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Modelling Resilience to Food Insecurity

Malawi Case Study

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Declaration

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Abstract

Defining “resilience to food insecurity” as a reference metric, allow governments and development partners to profile and rank a population in terms of their capacity to recover from shocks, and ultimately to evaluate programme impact. Quantifying a metric that captures multiple aspects of ones’ livelihoods, is still largely under discussion, due to the complex nature of the term and contextual differences across a range of countries.

Resilience is quantified following a mathematical approach that systematically describes recovery in terms of partial descriptors, called resilience metrics. Resilience to food insecurity metrics are derived from the trend of a composite food security indicator, the Food Consumption Score, which is simulated using mobile food security survey data collected in Malawi.

The model results from the Malawi case study correspond to previous food security analyses, where the resilience metrics describing a populations’ recovery capacity, supplement resilience to food insecurity analysis and may be used to inform food aid intervention. The resilience to food insecurity model, which may be applied in any context, is used to rank the regions in Malawi, according to the populations’ quantified resilience to food insecurity metrics.

Opsomming

Deur "veerkragtigheid tot voedselonsekerheid" as 'n verwysingsmaatstaf te definieer maak dit vir regerings- en ontwikkelingsvennote moontlik om 'n populasie se profiel te bepaal en die populasie te rangskik in terme van hul kapasiteit om van skokke te herstel, om uiteindelik program impakte te kan evalueer. Die kwantifisering van 'n maatstaf wat veelvuldige aspekte van 'n persoon se lewensbestaan vasvang, is nog onder bespreking, as gevolg van die komplekse aard van die term en kontekstuele verskille oor 'n verskeidenheid van lande.

Veerkragtigheid word gemeet met behulp van 'n wiskundige benadering wat sistematies die herstel beskryf in terme van gedeeltelike beskrywers, wat veerkragtigheidsmaatstawwe genoem word. Veerkragtigheidsmaatstawwe met betrekking tot voedselonsekerheid word afgelei van die tendens van 'n saamgestelde aanwyser vir voedselsekuriteit, die Voedselsekuriteitstelling, wat gesimuleer is deur gebruik te maak van mobiele voedselsekuriteitsopnamedata wat in Malawi ingesamel is.

Die modelresultate van die Malawi gevallestudie stem ooreen met vorige voedselsekuriteits analise, waar die veerskragtigheidsmaatstawwe wat 'n populasie se herstelvermoë beskryf, bykomstig is tot veerkragtigheid van voedselonsekerheidsanaliese, en gebruik kan word om ingrepe in voedselhulp in te lig. Die voedselonsekerheid-veerkragtigheidsmodel, wat in enige konteks toegepas kan word, is gebruik om die streke in Malawi te rangskik volgens die populasie se gekwantifiseerde voedselonsekerheidsmaatstawwe.

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List of Acronyms

BCCG: Box-Cox Cole and Green

BCPE: Box-Cox Power Exponential

CART: Classification and regression tree

CATI: Computer-assisted telephone interview

CFSVA: Comprehensive Food Security and Vulnerability Analysis

CoBRA: Community Based Resilience Analysis

CDF: Cumulative Distribution Function

CRF: Cumulative Resilience Function

CRS: Catholic Relief Services

CSI: Coping Strategy Index

FA: Factor analysis

FAO: Food and Agriculture Organization

FCS: Food Consumption Score

FSIN: Food Security Information Network

FNS: Food and nutrition security

GA: Gamma distribution

GEF: Global Environmental Facility

GG: Generalised gamma distribution

GoM: Government of Malawi

IBM: Individual-based model

ICA: Integrated Context Analysis

IG: Inverse Gaussian distribution

IDE: Integrated Development Environment

IPC: Integrated Food Security Phase Classification

IT: Information technology

IV: Instrumental variable

IVR: Interactive voice response

MIRA: Measurement Indicators for Resilience Analysis

MIMIC: Multiple Indicators Multiple Causes

ML: Maximum likelihood

ODD: Overview, Design concepts and Details

OLS: Ordinary least squares

PCA: Principal component analysis

PDF: Probability Density Function

PMF: Probability Mass Function

RCI: Resilience Capacity Index

RDF: Resilience Density Function

RIMA: Resilience Index Measurement and Analysis

RSM: Resilience Structure Matrix

RTD: Real-time data

SCTP: Social Cash Transfer Programme

SEM: Structural equation model

SIMI-R: Structurally Integrated Matrix of Indicators for Resilience

SMS: Short-Message-Service

TLU: Tropical Livestock Units

UN: United Nations

UBALE: United in Building and Advancing Life Expectations

UNDP: United Nations Development Programme

VAM: Vulnerability Analysis Mapping

WEI: Weibull distribution

WFP: World Food Programme

Glossary

Food security To have physical and economic access to sufficient safe and nutritious food that meet the dietary needs and food preferences for an active and healthy life [25].

Risk The system states' sensitivity to disturbances that could cause consequences [10].

Vulnerability The magnitude of fragility to the system [10].

Resilience The ability of the systems to return to a favourable state after a disturbance [16].

Resilience to food insecurity The ability to keep with a certain level of food security by withstanding shocks and stressors [2].

System A purposeful, organised structure with interdependent and interrelated components, that continually influence one another to maintain their activity and existence, to achieve an overall goal [29].

CHAPTER 1

Introduction

"There is no security without peace, and no peace without food."

- Ertharin Cousin, *WFP former Executive Director [9]*

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Food security, as defined by the United Nations (UN), is "the condition in which all people, at all times, have physical, social and economic access to sufficient safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life" [25]. The 2019 Global Report on Food Crises estimated that 113 million people, in 53 countries, are food insecure and require urgent livelihood, food and nutrition assistance [30].

Included in the 2019 estimation, is one of Southern Africa's low-income, land-locked countries, Malawi, accounting for an estimated 3.3 million food insecure people. With a population of just over 19 million people, 17 percent of Malawians are classified as food insecure [30]. Food insecurity in Malawi is largely attributed to climatic shocks, particularly drought and floods, as 80 percent of Malawians are smallholder farmers who rely on rain-fed agriculture for food [32].

Resilience to food insecurity is a popular topic of discussion between the Government of Malawi (GoM) and their international development partners, as it uncovers a promising framework for profiling a population in terms of their capacity to recover from shocks [16]. Discussions, particularly among UN agencies such as the Food and Agriculture Organisation (FAO) and the World Food Programme (WFP), are aimed at defining a reference metric that captures multiple aspects of livelihoods, to evaluate programme impact on a populations' food security.

Proposed resilience to food insecurity models are still under discussion, due to the complex nature of the term and contextual differences, in terms of the type and scope of shocks, as defined in §1.1. The problem description and objectives of the study are described in §1.2.

1.1 Defining resilience to food insecurity

Food security relates to food procurement capabilities and concerns food availability, access to food, food utilisation and stability, as outlined in §1.1.1. Resilience to food insecurity relates to ones' ability to maintain an acceptable level of food security, as outlined in §1.1.2.

1.1.1 Comprehending food security

Food availability refers to the "supply side" of food security and concerns food production, stock levels and net trade. Access to food refers to the assets needed to consume food and concerns income, expenditure and market prices. Food utilisation is the extent to which food is effectively transformed by the body and concerns feeding practices, food preparation, diversity of the diet and intra-household distribution. Stability refers to the long-term maintenance of consumption levels and concerns weather conditions, political instability and economic factors [11].

Food security is often analysed in terms of vulnerability to food insecurity and can be defined in terms of two perspectives; from the exposure to risks or from the inability to manage risks. Development actors may intervene by reducing ones' exposure to risks or by strengthening their ability to cope. The World Bank, for example, focuses on minimising a communities' exposure to risk, where the UK Department for International Development focuses on strengthening ones' ability to cope and the assets required to sustain livelihoods [26].

A sustainable livelihood approach to analysing food insecurity identifies vulnerable groups in terms of their geographic location to determine the causes of vulnerability. Metrics such as wasting, stunting and underweight, reflect the consequences of prolonged food insecurity. Other metrics include those living on less than a dollar a day or consuming less than the recommended calorie intake [21].

Other than seasonal food insecurity, with a predictable cyclical nature, two general types of food insecurity, based on the duration of a situation, are chronic and transitory. Long-term chronic food insecurity occurs over a sustained period of time due to inadequate access to resources [11]. Short-term transitory, or acute, food insecurity occurs when there is a sudden drop in food accessibility.

The severity of a situation influences the nature and urgency of assistance, and is often classified into phases using selected metrics. The Integrated Food Security Phase Classification (IPC), for example, uses indicators including livelihood assets, food and water access and availability, coping strategies, dietary diversity and malnutrition prevalence metrics to analyse food security [11]. Common indicators used to model food security are summarised in Table A.1 and Table A.2.

Malnutrition refers to the imbalanced intake of macro/micro-nutrients and covers two conditions, namely, undernutrition and overnutrition. Undernutrition covers micro-nutrient deficiencies, wasting, stunting and underweight. Overnutrition covers overweight, obesity and diet-related non-communicable diseases, such as diabetes, stroke, heart disease and cancer [17].

Food security and nutrition security, often stated as food and nutrition security (FNS), work hand-in-hand, in that someone who is food insecure, is unavoidably nutrition insecure. Food security is a necessary but not sufficient condition of nutrition security [26]. Someone who is food secure may be nutrition insecure, due to lack of breast feeding, inadequate hygiene or infectious diseases, such as pneumonia, malaria, or measles, which increases their nutrient requirements.

1.1.2 Conceptualising resilience

Resilience, proposed in 19^{th} century shipbuilding, to calculate the capacity of materials to absorb changes in loads, without breaking, comes from the Latin word resilire, meaning "to recoil" [10].

In civil and mechanical engineering, the modulus of resilience, is the "maximum amount of energy that can be absorbed without creating a permanent distortion." Ecologists define resilience as the "amount of disturbance a system can absorb before shifting into an alternative state", while psychologists define resilience as the "reduced vulnerability to environmental risk experiences, the overcoming of a stress or adversity." Resilience, broadly defined as "the capacity that ensures adverse shocks do not have long-lasting adverse consequences", may be applied at different levels of aggregation, such as individuals, organisations or systems [16].

In supply chain management, vulnerability and resilience are two complementary concepts within risk management. Pettit [10] defines risk as "a combination of the system state and its' sensitivity to hazards that could cause damage", where vulnerability is the "degree of fragility to the system", and resilience is "the systems ability to return to a favourable state after disturbance".

Risk management identifies strategies for handling risks in uncertain environments. Vulnerability deals with risk exposure, where resilience deals with the ability to know what to expect, what has happened, what to look for and what to do [10]. Pettit validates that as capabilities increase, resilience increases and vulnerability decreases, and that risk, if managed, may be as much a source of gains as losses, thus may further increase resilience [10].

Resilience to food insecurity

Resilience to food insecurity is defined as "the ability to keep with an acceptable level of well-being by withstanding shocks" and is strongly impacted by the education, health and agriculture systems in place. Resilience to food insecurity concerns the setting in which one resides, the resources available, how one utilises those resources to consume food and improve nutritional status, and lastly, how resource utilisation is affected by shocks [16].

The setting in which one resides may be described by its' physical, social, legal, governance or economic characteristics [16]. Climate, geography, rainfall variability, soil fertility, distances to markets, access to safe water, and quality of infrastructure are all components of the physical setting. Notions of correct behaviours, norms of gender roles and folk wisdom form part of the social setting, as well as the existence of trust, reciprocity, social cohesion, and strife. The legal setting affects economic exchange and how one uses their resources. The governance setting includes the political processes that centralise or decentralise dictatorial or democratic processes. The economic setting captures policies that affect the level and variability of return on assets.

Resources may be divided into two categories, namely, time and capital. Time refers to physical labour for work, while capital refers to assets, knowledge and physical health. Assets include financial resources, land, livestock, social capital and tools for production, that when combined with labour, generate income. Knowledge includes formal education and physical health includes nutritional status. Resources, such as education and health, are individually owned, whereas others, such as land and financial capital, may be individually or collectively owned [16].

Resource utilisation refers to ones' livelihood strategy and concerns food production, cash crop production, livestock, and non-agricultural income-generating activities. Income affects what resources are available for food consumption, other goods, savings and human capital formation such as health, nutrition and education. Resource utilisation may be affected by shocks that are covariant (impact many) or idiosyncratic (impact a few). Shocks may be isolated, rapid-onset events, such as floods, or stressors resulting from long-term processes, such as drought [16].

The fundamental challenge with modelling resilience to food insecurity, as described in §1.2, involves evaluating a complex set of interacting food security variables, across a range of contexts.

1.2 Problem statement

Development actors require a metric for resilience to food insecurity to evaluate programme impact across a range of contexts, such as different countries, for example, or concerning different types of shocks. A number of resilience to food insecurity models have been proposed to evaluate a range of food security programmes, many of which have been applied in Malawi. The models however, present a trade-off between the frequency of data collection and the volume of data processing, as they account for a complex set of interacting influences.

A composite food security metric that is captured using mobile technology allows for wide-scale frequent data collection. Quantifying resilience to food insecurity in terms of such a metric, allows for comparability across a range of contexts. Mobile survey data, collected in Malawi, may demonstrate how a proposed resilience to food insecurity model, may be used to quantify and rank a population in terms of their recovery capacity.

1.2.1 Objectives

This study sets to achieve three key objectives:

1. Describe a food security indicator that captures the effect of multiple livelihood capabilities on a populations' food consumption. Ensure the indicator may be collected using mobile technology, to enable frequent, wide-scale data collection, suitable for resilience analysis.

2. Develop a food security simulation model to monitor and estimate a populations' food security situation, and to determine the amount of food aid required for a populations' food consumption to recover from a simulated shock.

3. Define a set of resilience to food insecurity metrics, that quantify a populations' ability to recover to an acceptable level of food security, and enable development actors to rank a population, in terms of their recovery capacity.

4. Demonstrate how the simulation model can be used to assess the food insecurity status of a population by applying it to a Malawi case study.

1.2.2 Assumptions

This study makes the following notable assumptions:

1. The Food Consumption Score (FCS) metric reflects an individuals' current food security situation and is considered to be the result of countless livelihood capabilities.

2. Modelling resilience to food insecurity concerns the change in a selected food security variable, specifically the FCS, rather than the change in influencing latent variables.

3. The Malawi survey data applied in the simulation, is considered to be representative of the population, and is used for demonstrative purposes rather than policy guidance.

4. The selected impact of the simulated shock is defined for the case study example, but may be adjusted in the model. The selected shock impact is defined for demonstrative purposes and is not based on historical shock data.

5. Single shock occurrence is considered, with all people affected similarly, not differentiated on region or distance to shock epicentre.

6. Aid is made available to all in need, not considering distribution point locations or distances to distribution points. Aid may be made available at different levels for regions. No upper limit is set on aid availability.

7. The simulated data represents the food security situation following a shock, even though the underlying collected data used in the model was collected at a time when no significant shock had recently occurred.

1.3 Layout of the document

Previous food security analyses and resilience to food insecurity modelling methods are discussed in Chapter 2, with particular focus on the methods applied in the selected case study country, Malawi. The proposed food security model developed to quantify resilience to food insecurity, is defined in Chapter 3, followed by the applied survey data from Malawi and model results, in Chapter 4. The study outcomes and lessons learned are concluded in Chapter 5.

CHAPTER 2

Literature

"Give a person a fish and they will eat for a day. Teach that person to farm and the whole neighbourhood will get tomatoes."

- Proverbial phrase [23]

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A populations' recovery capacity is dependent on a range of capabilities, influenced by income, assets such as land and livestock, and access to food, basic services and social protection [11].

Various food security analysis and resilience to food insecurity analysis models, as discussed in §2.1 and §2.2, respectively, have been proposed to quantify the impact of capabilities on a populations' food security. Resilience modelling limitations, as discussed in §2.3, are due to the data requirements and collection methods employed. The food security analysis and resilience to food insecurity analysis models applied in Malawi, as reviewed in §2.4, exhibit the limitations of current resilience to food insecurity models. A systems analysis approach to modelling resilience to food insecurity, as discussed in §2.5, addresses the limitations of such models, in analysing resilience to food insecurity. Finally, the identified research gaps, as discussed in §2.6, highlight the study objectives and suggest future research considerations.

2.1 Food security analysis models

Analysing a populations' food insecurity primarily concerns their vulnerability to food insecurity and considers their exposure to risks, and secondarily concerns their resilience to food insecurity and considers their ability to manage risks, as discussed in §2.2.

Vulnerability analyses help development actors identify programmatic strategies to strengthen the food security of populations most vulnerable to food insecurity [37]. Vulnerability to food insecurity analyses are often conducted at a national scale to help development actors identify population groups that are most vulnerable to food insecurity.

An international food security classification standard, applied by development actors to identify food insecure populations across a range of contexts in Latin America, Africa and Asia, includes the Integrated Food Security Phase Classification (IPC), originally developed in 2004 by the Food and Agriculture Organisation, to analyse food insecurity in Somalia.

The IPC considers information describing a range of topics, including food consumption, coping strategies, nutrition, markets, natural disasters and the socio-economic context, as summarised in Table A.1 and Table A.2, to categorise a population into food insecurity severity phases [18].

An Acute IPC analysis assesses a populations' current food security situation and categorises population groups into five food insecurity severity phases, namely, minimal, stressed, crisis, emergency and famine phase [18]. A Chronic IPC analysis assesses a populations' long-term food security situation and categorises population groups into four food insecurity severity phases, namely, minimal, mild, moderate and severe phase [18].

A Comprehensive Food Security and Vulnerability Analysis (CFSVA) model, conducted by the World Food Programme (WFP), analyses responses from an integrated household survey [36]. By identifying who is vulnerable to food insecurity, how many food insecure people there are, where they live and why they are food insecure, the analysis sets to address the root causes of food insecurity and to determine the appropriate type of assistance required to reduce vulnerability to food insecurity [36].

The CFSVA baseline survey considers information describing a range of topics, including food consumption, food supplies, livelihoods, nutrition, coping strategies, markets, natural disasters, production and education, as summarised in Table A.1, Table A.2 and Table A.4, to help identify and describe food insecurity trends.

An Integrated Context Analysis (ICA) model, also conducted by WFP, considers the findings from previous food insecurity analyses, such as the IPC and CFSVA, and analyses historical trends of food security and shocks, to describe a populations' exposure to risk and help prioritise programmatic strategies such as disaster risk reduction, resilience building and social protection programmes [37].

A number of food security analysis models, particularly the IPC, CFSVA and ICA, consider food consumption as a fundamental food security indicator. A particular proxy metric for food security, developed by WFP in 1996, is the Food Consumption Score (FCS), which is used to evaluate the diversity and frequency of usual household diets [37], as defined in §2.1.1.

2.1.1 Food Consumption Score

The FCS is calculated by multiplying a respondents' consumption frequency of food from eight food groups, in the prior seven day period, with standardised weights, reflecting the food in the food groups respective nutrient densities, as outlined in Table 2.1 and illustrated in Table 2.2 and Table 2.3.

> *"How many days in the past seven days did your household eat food from the following food groups?"*

Food group	Food item examples	Weight
Oils and fats	butter, margarine, vegetable oil	0.5
Sugar	cake, honey, jam, sugar	0.5
Fruits	apples, apricots, avocados, bananas, lemons, guava, mangos, papaya, peaches, oranges	1
Vegetables	beans, carrots, mushrooms, okra, onions, orange sweet potatoes, pumpkin, tomatoes	1
Cereals, grains, roots and tubers	bread, cassava, maize, potato, pasta, sorghum, rice, white sweet potatoes	2
Pulses and nuts/seeds	lentils, nuts, peas, peanuts, sugar beans, soy	3
Dairy	cheese, milk, yoghurt and other milk products	4
Meat, eggs and fish	beef, bush meat, chickens, eggs, fish, goat, organ meat, pork	4

Table 2.1: *Food groups, food items and weights applied in the food consumption score calculation [37].*

Food group	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Frequency
Oils and fats	oil	oil	oil	oil	oil butter	butter	butter	7
Sugar		sugar jam		sugar	sugar	sugar	sugar	5
Fruits					peach	banana peach	banana peach	3
Vegetables	beans	onion	beans	beans onion				4
Cereals, grains, roots and tubers			bread rice	bread maize				2
Pulses and nuts/seeds	peas	peas						2
Dairy			milk cheese			milk	milk	3
Meat, eggs and fish					fish			1

Table 2.2: *Weekly food diary example illustrating how the Food Consumption Score is calculated.*

Food group	Consumption frequency (days)	Weight	Score
Oils and fats	7	0.5	3.5
Sugar	5	0.5	2.5
Fruits	3	1	3
Vegetables	4	1	4
Cereals, grains, roots and tubers	2	2	4
Pulses and nuts/seeds	2	3	6
Dairy	3	4	12
Meat, eggs and fish	1	4	4
		Food Consumption Score:	39

TABLE 2.3: *Example illustrating how the Food Consumption Score is calculated.*

For example, only the number of days matter, not the amount of a specific food item per day that counts, as shown in Table 2.2 and Table 2.3. The variety of a food items in one food group per day is not considered, rather the variety of food groups eaten over different days is considered.

Food groups consumed in small amounts, for example less than a tablespoon, are not counted [33]. Meals that are consumed in public kitchens or private restaurants are not considered, since the FCS is used to reflect the usual household diversity and frequency, where restaurant meals may not necessarily be consumed frequently or by every person in the household.

The advantages of using the FCS as a proxy metric for food security include the ability for frequent and wide-scale data collection through electronic surveys using mobile technology as well as the applicability of the questions across multiple contexts.

A limitation of the FCS is that it does not account for meal portion sizes nor the number of meals per day, thus if a household is limiting their meal portion sizes or decreasing the number of meals eaten per day, a constant FCS will not reflect the actual decrease in weekly food consumption. The FCS may be analysed in conjunction with the coping strategy index (CSI), which asks what strategies a household employs when it does not have enough food. Different strategies are given weights according to the severity of each, to indicate whether the households' food security status is declining or improving over time.

2.2 Resilience to food insecurity analysis models

A growing number of resilience to food insecurity analyses have been modelled, tested and adapted, by many government partners and developments actors, in various contexts over the years, to guide and evaluate the impact of food security programmes.

Resilience to food insecurity analyses help development actors assess a populations' recovery capacity, to prioritise the populations that are least resilient to food insecurity, for food security programming interventions. Analyses are often conducted on a small scale, for example at a district level, to evaluate programmatic strategies that have been implemented to strengthen food security [19].

The Resilience Index Measurement and Analysis (RIMA) model, first proposed in 2008 by the Food and Agriculture Organisation (FAO), evaluates resilience to food insecurity using an econometric model. Key food security analysis components, named pillars, that are considered include income and food access, assets, access to public services, social safety nets and adaptive capacities, as summarised in Table A.3.

The considered analysis components are evaluated using factor analysis (FA) methods, principal component analysis (PCA) and optimal scaling. A classification and regression tree (CART) is then used to derive a resilience capacity index (RCI) [2]. An adapted 2014 RIMA model uses a structural equation model (SEM) to derive the RCI, where a 2015 RIMA-I model uses ordinary least square (OLS) and instrumental variable (IV).

A further adapted 2016 RIMA-II model uses Multiple Indicators Multiple Causes (MIMIC) and maximum likelihood (ML) to derive the RCI, and regression analysis to derive a resilience structure matrix (RSM). Adapted RIMA models have been applied to evaluate food security programmes in a number of countries, including Palestine, Niger, Mali, Burkina Faso, Tanzania, Uganda and Malawi [3].

The Measurement Indicators for Resilience Analysis (MIRA) model, proposed by the Catholic Relief Services in 2017, considers metrics describing three topics, namely, well-being outcomes, shocks, and capacities, to assess the recovery of selected metrics over time. Well-being outcomes include FCS, dietary diversity, CSI, and assistance needed. Shocks include covariate shocks, such as epidemics, floods or drought, and idiosyncratic shocks such as chronic illness, loss of a family member or crop disease. Capacity metrics include land, number of houses, age, gender, education and tropical livestock units [19], as summarised in Table A.4.

The RIMA models and MIRA model all evaluate a populations' resilience to food insecurity, using various deterministic models, and a range of latent variables, that are collected at discrete points in time, as discussed in §2.3.1.

The Structurally Integrated Matrix of Indicators for Resilience (SIMI-R) model, first proposed by the Food Security Information Network (FSIN) in 2015, clusters comparable food security indicators into groups to harmonise comparisons of data elements across studies, location and time. The SIMI-R model makes use of PCA and multivariate regression methods to specify indicator categories [7].

The Community Based Resilience Analysis (CoBRA) model, proposed by the United Nations Development Programme (UNDP) in 2017, is a qualitative assessment that conducts a number of community group-discussions to consider the views of local communities on resilience building activities, and to inform expert-led resilience planning and programming efforts [22].

The CoBRA model analyses qualitative data to describe a populations perception of their own resilience, rather than evaluating a resilience to food insecurity metric or resilience to food insecurity index. Both the CoBRA and SIMI-R model are not suitable for evaluating a populations' resilience to food insecurity continuously over time, as analyses are conducted at discrete points in time.

A major disadvantage of the discussed resilience to food insecurity analysis models in evaluating a populations resilience, is the data collection requirements, which hinders the frequency of data collection, as discussed in §2.3. Resilience analysis favours the application of time series data of a single variable over discrete data of multiple variables, as discussed in §2.5.

2.3 Data requirements and collection methods

The data requirements of previous food security analysis models, particularly the IPC and CFSVA, and resilience to food insecurity analysis models, particularly the RIMA and MIRA models, as discussed in §2.3.1, cover a range of topics. The data collection methods employed to collect the required data, as discussed in §2.3.2, hinder the possible frequency of data collection.

2.3.1 Data requirements

Food security analyses are generally conducted to identify food insecure populations and the root causes of food insecurity, thus the assessments are more comprehensive in nature, and consequently less frequent.

The IPC analyses information describing a range of topics, including, food consumption, dietary diversity, coping strategies, nutrition, natural disasters and the socio-economic context [18]. The CFSVA analyses information describing food consumption, food supplies, livelihoods, nutrition, coping strategies, markets, natural disasters, production and education [36], as summarised in Table A.1, Table A.2 and Table A.4.

Previous resilience to food insecurity analysis models developed and applied to evaluate food security programming, particularly the RIMA models and MIRA model, also consider a range of variables describing different topics, as summarised in Table A.4.

The RIMA model and adapted RIMA models, require a wide range of variables describing the key analysis components, namely income and food access, assets, access to public services, social safety nets and adaptive capacities, including expenditure, sanitation, electricity, land, crops, seeds, vehicle assets, shock exposure, cash transfers, education and livelihoods [3], as outlined in Table A.3.

The MIRA model requires a wide range of variables describing well-being outcomes, shocks and adaptive capacities, such as FCS, livelihoods, expenditure, CSI, hunger score, assistance needed, epidemics, floods, drought, crop disease, land, number of houses, age, gender and tropical livestock units [19], as summarised in Table A.4.

A wide range of data requirements, such as that required for the IPC and CFSVA models, impacts the frequency and scale of data collection, as discussed in §2.3.2. The data requirements covering a wide range of topics, such as that required for the RIMA and MIRA models, may impact the comparability of data that is collected across a range of contexts, due to a high chance of data requirement gaps.

Comparing resilience to food insecurity in Tanzania to that in Mozambique, for example, may be challenging if data collected in Tanzania is collected differently in Mozambique, with regards to the frequency, scale, coverage of topics or even the mode of data collection.

Moreover, the data applied to describe a populations' education, and the data applied to describe their livelihoods, for example in a RIMA model to analyse food insecurity in a single selected country, may not necessarily have been collected at the same points in time, or even collected at the same scale from the same sample population.

2.3.2 Collection methods

The Acute IPC analysis, which analyses a populations current food insecurity situation, is conducted in a selected food insecure country, on an annual or biannual basis, where the Chronic

IPC analysis, which analyses a populations' long-term food insecurity, is conducted in a selected country every five or so years [18].

The IPC analyses are conducted at a national scale in over 30 food insecure countries across Africa, Latin America and Asia, to enable food security programming comparisons, through the use of a standardised food insecurity indicator. The IPC may be used to inform governments and their international development partners', such as FAO or WFP, on programmatic strategies to reduce food insecurity [18].

The CFSVA is conducted at a national scale in a selected country, particularly crisis prone and food insecure countries where WFP has implemented food security programmes, for example Iraq or Malawi, once off or on a biennial basis [36]. Data collection often includes conducting household surveys, which involve a group of enumerators visiting a sampled range of households across the selected country. Data collection, processing, analysing and reporting can take a number of months to complete, thus it is difficult to collect and compare monthly, or even weekly data, especially at a national scale.

Data collection involving "boots-on-the-ground", where a number of enumerators are required to undertake multiple field trips across the country to conduct household surveys, may be costly due to the enumerator compensation, enumerator training costs, hiring of vehicles, fuel and maintenance as well as the survey capturing devices used, for example if each enumerator records responses using an iPad.

To counteract the natural trade-off between the cost, frequency, scope and scale of such analyses, WFP collects high frequency food security data using mobile technology, to monitor real-time food security trends [33]. Remote mobile data collection methods include Short-Message-Service (SMS) surveys, interactive voice response (IVR) technology and computer-assisted telephone interviews (CATI). Questionnaires are tailored to individual countries and designed to capture relevant, timely and frequent information required to implement food security programmes, as demonstrated in Appendix B.1.

The RIMA models consider data covering a range of topics, where the use of secondary data is recommended. Data describing selected food security indicators may be taken from previous national food security survey, such as integrated household surveys or demographic household surveys.

The data required for the MIRA model is generally collected on a monthly basis, where the survey enumerators visit the same households each month, to conduct a 15 minute face-to-face food security survey [19].

A systems analysis approach to modelling resilience, as described in §2.5, nullifies the need for extensive data collection requirements, as it concerns the change of a single selected system state variable over time. Previous food security and resilience to food insecurity analyses applied in the case study country, Malawi, as discussed in §2.4, demonstrate the highlighted limitations of data collection requirements in previous resilience food insecurity analysis models.

2.4 Food Security and Resilience studies in Malawi

Since 2015, the Government of Malawi (GoM) has declared a state of emergency on three occasions: in January 2015, following a flooding crisis [13], in April 2016, following the countries' worst drought in 35 years [12], and in March 2019, following the flooding crisis [14].

Responding to shocks in Malawi, while improving the countries' food security, has been on development actors' agenda for years, where a number of food security analyses, as discussed in §2.4.1, have been conducted by various development actors, to help inform food security programming. Resilience to food insecurity analyses in Malawi, as discussed in §2.4.2, have been conducted in selected districts across the country, to help evaluate food security programming interventions and to monitor a populations' recovery capacity.

2.4.1 Food security assessments in Malawi

The Acute IPC, an international standard scale to evaluate the magnitude of current food insecurity, was piloted in Malawi in 2009, where the Chronic IPC was piloted in 2012. In 2017, the United Nations (UN) Malawi team accepted the IPC as the primary source of food security information to help mitigate food insecurity [30].

The March 2019 Acute IPC report, indicated that majority of Malawians are in a phase 2 and phase 3, or a stressed and crisis, food insecurity situation, as shown in Figure 2.1. The Northern Region, which has a considerably lower population, around 2 million, than the Central Region and Southern Region, around 8 million in each region [6], is predominantly in a minimal food security situation, as shown in Figure 2.1. The food insecurity situation in the Southern Region is predominantly in a crisis situation, while the Central Region is in a crisis situation towards the south and a stressed situation towards the north [30].

Since the IPC was piloted in 2009, a number of other food security analyses have been conducted in Malawi by GoM and their development partners, to better inform food security programming and food security intervention targeting.

A CFSVA, conducted by WFP in Malawi in 2010, reported similar findings, where poor food consumption was most prevalent in the south-eastern part of the country, and acceptable food consumption was most prevalent in the north-western part of the country. Among the households in the Middle Shire Valley zones, borderline consumption was most prevalent [35].

A CFSVA, conducted again in 2012, reported that the percentage of households in Malawi facing food shortages was, over 37 percent in the Northern Region, over 47 percent in the Central Region and over 53 percent in the Southern Region. Seasonal food shortages typically start in November and last until March, where majority of households attribute shortages to erratic rains and dry spells [36].

A 2014 Malawi ICA, also conducted by WFP, estimated from food insecurity trends, that the average number of people who were vulnerable to food insecurity, between 2009 and 2013, was around 298 000 in the Northern Region, 461 000 in the Central Region and 889 000 in the Southern Region [37]. The 2014 ICA indicates that districts in the Southern Region are more prone to climatic shocks such as drought and flooding, than districts in the Northern Region and Central Region.

The food security analyses conducted in Malawi, particularly the IPC, CFSVA and ICA, indicate that the Southern Region is generally more vulnerable to food insecurity, than the Northern Region and Central Region [30] [36] [35] [37].

The national food security analyses are comprehensive and consider a wide range of variables, thus require a lengthy and costly data collection period, and are therefore difficult to conduct on a monthly basis, as discussed in §2.4.3.

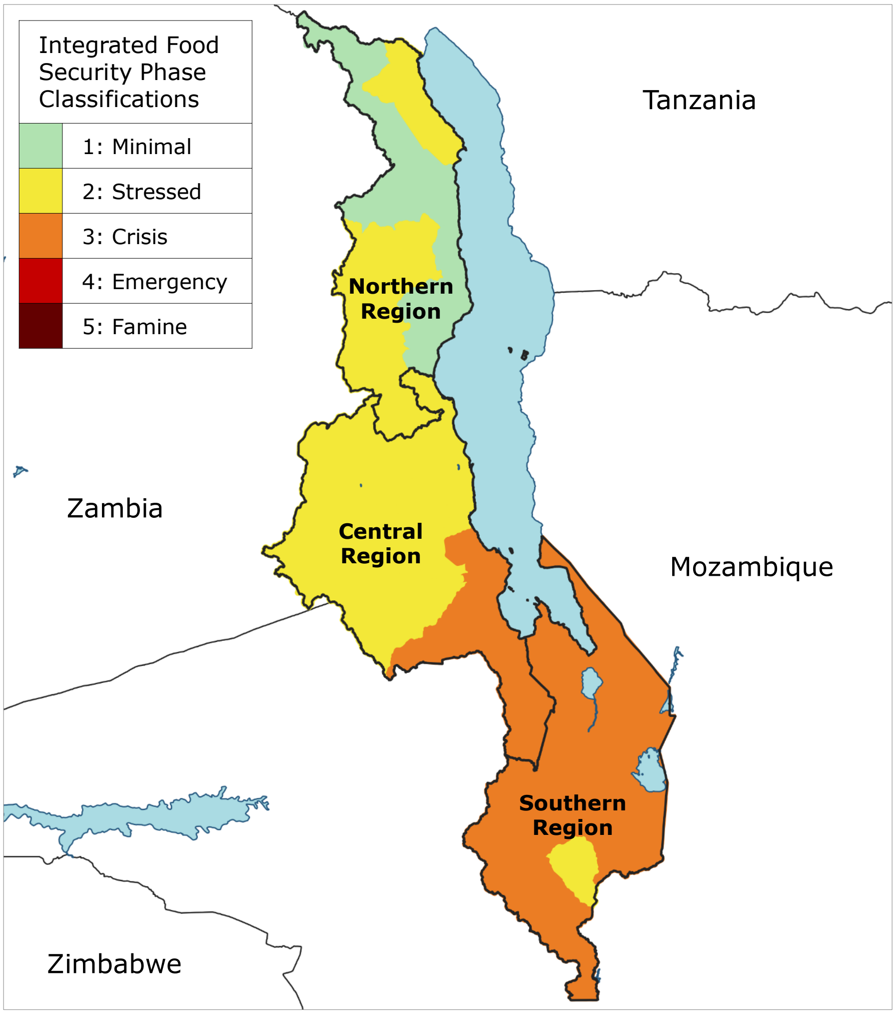


FIGURE 2.1: *Acute Integrated Food Security Phase Classification in Malawi, October 2018 to March 2019 [30].*

2.4.2 Resilience studies in Malawi

A number of resilience to food insecurity analyses have been conducted in districts across Malawi, to help the GoM and their development partners evaluate a range of selected food security programming interventions, as illustrated in Figure 2.2.

A 2016 CoBRA study, was conducted in two districts in the Southern Region, namely, Machinga and Mangochi, to guide a Climate Proofing Local Development Gains Project. A 2017 CoBRA study, was conducted in a district in each region, namely, Nkhata Bay, Zomba and Ntcheu, to guide a Global Environment Facility (GEF) resilience project [22], as illustrated in Figure 2.2.

A 2016 unconditional Social Cash Transfer Programme (SCTP), was implemented in a district in the Central Region and Southern Region, namely, Salima and Mangochi, respectively [31], as illustrated in Figure 2.2. The project was guided by a RIMA-II analysis to target labour constrained households, reduce hunger and increase school enrolment rates.

A 2017 MIRA model, was applied to three disaster prone districts in the Southern Region, namely, Chikwawa, Nsanje and Rural Blantyre, as illustrated in Figure 2.2, to assess the impact of a United in Building and Advancing Life Expectations (UBALE) programme, on beneficiaries' resilience to food insecurity [19].

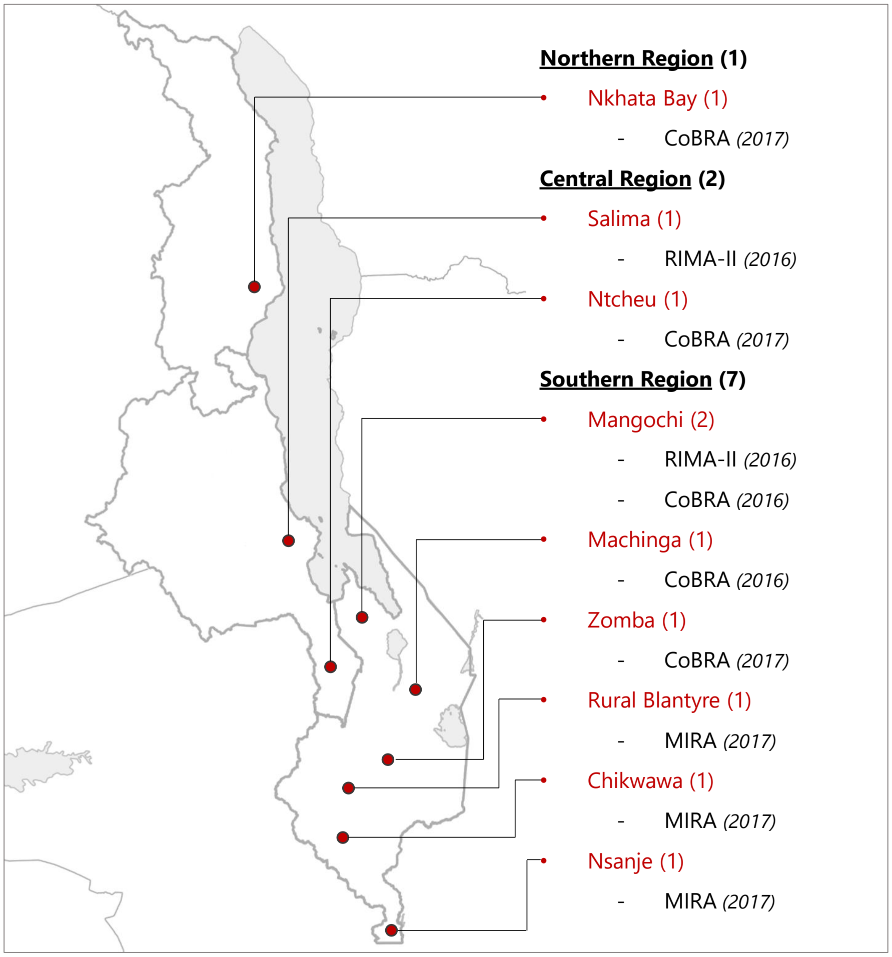


FIGURE 2.2: *Resilience to food insecurity analyses conducted in Malawi.*

The data collections methods used for the food security and resilience to food insecurity analyses, as discussed in §2.4.3, are not only costly in terms of funding and time requirements, but present a trade-off between the comprehensiveness and the frequency of collected data.

Where food security analyses are conducted at a national scale to help identify where resilience strengthening programmes should be implemented, resilience to food insecurity analyses are conducted at a smaller concentrated scale, specifically where resilience building activities have been implemented. Majority of the resilience to food insecurity analyses conducted in Malawi, have been conducted in districts in the Southern Region, as shown in Figure 2.2.

2.4.3 Food security data collection in Malawi

Data collection for the food security analyses conducted in Malawi, particularly the CFSVA, is generally a lengthy process, as national scale assessments require a number of enumerators to undertake field trips to conduct up to 5 000 household surveys [35]. Resilience to food insecurity analyses applied in Malawi, particularly RIMA-II, make use of secondary data.

Prior to data collection, enumerator training is conducted in order to ensure all the surveys are conducted accordingly and in the correct sampled zones. Data processing is also a lengthy process as responses are both quantitative and qualitative, where interpretations and results are validated through a large assessment committee [35].

Responses are collected from a range of stakeholders, including head of households, farmers, market traders, village chiefs and Ministers of Agriculture. Responses may be collected using iPads or pen and paper, as shown in Figure 2.3, where electronic capturing, such as using an iPad, speeds up data processing, thus allows for more frequent data collection.

(a) *A* 2019 *comprehensive household food security survey conducted by an enumerator, using an iPad to collect survey responses.*

(b) *A group discussion with farmers, where the repondents demonstrative explanations are captured using pen and paper, to allow for descriptive free response answers, for example, where the farmers may use beans to describe and discuss concepts such as income expenditure or crop yield.*

Figure 2.3: *Data collection methods used for the Malawi Vulnerability Assessment Committee* 2019 *national food security analysis.*

To increase the frequency and scale of data collection, in 2017 WFP conducted CATI surveys in Malawi, as illustrated in Appendix B.1, to monitor real-time food security trends following the 2015 and 2016 El Niño induced drought [33]. A particular question asked captures a household's food consumption diversity and frequency, required to calculate the FCS.

Remote mobile data collection methods that use a computerised interview, such as CATI, as shown in Figure 2.4, allows for more timely data collection and frequent data capturing, required to implement food security programmes. Although CATI is a cheaper data collection method than household surveys, due to the lack of enumerator costs, including training, survey capturing devices, transport, accommodation and food costs for a number of field enumerators, the Malawi CATI surveys were concluded after four months [33].

Modelling food security following a systems analysis approach, as discussed in §2.5, demonstrates how resilience to food insecurity may be quantified using a single composite indicator, and thus reduce the data collection requirements, which allows for more frequent data collection.

FIGURE 2.4: *Mobile technology data collection methods used in Malawi [34].*

2.5 Modelling the resilience of systems

Modelling food security necessitates systems analysis, as food procurement capabilities depend on interacting systems, such as the climate system for example, which is governed by the laws of physics and chemistry, as well as on social systems, which are governed by the laws of supply and demand [8]. The resilience of food systems may however, be modelled using simple calculus and probability theory methods.

Systems analysis concerns the interactions and resulting behaviour patterns of the components in a system, as outlined in §2.5.1. Resilience analysis concerns the change in a selected system state variable over time, following a shock, as outlined in §2.5.2.

2.5.1 Systems analysis

System, derived from the Latin word systēma, means "a regularly interacting or interdependent group of items forming a unified whole". In systems theory, a system is described as a purposeful collection of interrelated and interdependent components. Components continually interact with one another while reacting to changes in their environment, to maintain their activity, sustain the system, and achieve some overall purpose [29].

Systems have inputs, outputs and feedback mechanisms, and are expressed in terms of their spatial and temporal boundaries, influencing environment and overall structure and purpose. Feedback mechanisms allow systems to maintain an internal steady-state, called homeostasis, despite a continuously changing environment. Systems often display emergent properties, where the properties of the whole are not possessed by the individual components [29].

Systems may generally be divided into two categories, namely, closed systems and open systems. Closed systems, in theory, are not influenced by their surroundings, thus the system components' external environment is not considered. Open systems consider the exchange of information, energy and material with the system components' external environment, or rather, the larger system in which they operate [29].

A systems model may involve a diverse set of interacting components, with relationships that are not always precisely known, and may exhibit discontinuous and chaotic behaviour, due to a number of uncertain feedback mechanisms. Components are heterogeneous and indivisible, but may be organised into hierarchical or structured groups, which may influence the system behaviour [29].

A promising method that may be followed to model systems, is agent-based modelling (ABM). In ABM, an agent (system component) is given a set of rules that govern its' behaviour, and left to interact with other agents. Agents are decentralized and may form part of different networks that may not be made explicit. Flexible localised rules and alternative options allow agents to learn, innovate, reorganize, or reorientate [5].

Modellers analyse macro-scale patterns that emerge over time, to identify complex behaviour. Over time micro-level interactions may emerge into self-organised macro-level structures, such as markets for example, due to agents cooperating, coordinating or competing. Such structures feedback into the system and may stabilise or destabilise agents' future state [1].

Rather than modelling a complex range of interacting system variables, which would require intensive data collection, a single selected indicator variable that describes the changes in an agents' state, or a state variable, may be used to model the resilience of a system, as described in §2.5.2.

2.5.2 Resilience modelling

The outlined resilience of engineering systems model, proposed by Sharma et al [27], integrates the state of a system, following a disruption or a shock, with the recovery process of achieving a desirable state.

The system state is determined at any time in terms of the reliability, or the probability that a system meets a specified performance level. Higher values of reliability indicate that it is more probable that the system meets a specified performance level, and is dependent on the state of the system and the damage level at that time of interest [27].

Defined damage levels are delimited by means of three state thresholds: β_0, β_{acc}, and β_{tol}, as outlined in Table 2.4.

Damage level	Reliability-based definition
None (N)	Reliability does not change with respect to the original reliability ($\beta_0 \leq \beta$).
Insignificant (I)	Reliability decreases but remains above the acceptable threshold ($\beta_{\text{acc}} \leq \beta < \beta_0$).
Moderate (M)	Reliability decreases below the acceptable threshold but remains above a minimum tolerable threshold ($\beta_{\text{tol}} \leq \beta < \beta_{\text{acc}}$).
Heavy (H)	Reliability decreases below a minimum tolerable threshold ($\beta < \beta_{\text{tol}}$).

Table 2.4: *Damage levels and reliability-based definitions.*

A recovery curve, typically a non-decreasing function of time, represents the path of reliability over the recovery duration, as shown in Figure 2.5. Resilience is quantified using the integral of the recovery curve over time.

A shock at time t_I causes a reduction in the system state, represented by $Q(t)$. The system state immediately after a shock, Q_{res}, depends on the shock intensity and the system state pre-shock. The system subsequently undergoes recovery to achieve a desired $Q(t)$. Recovery terminates at time t_L, once the desired requirements are met [27].

The impact of resilience influencing factors, are reflected in the shape of the recovery curve and the recovery time, $T_R = t_L - t_I$. The resilience of the system is typically quantified as a function of the shaded area in Figure 2.5.

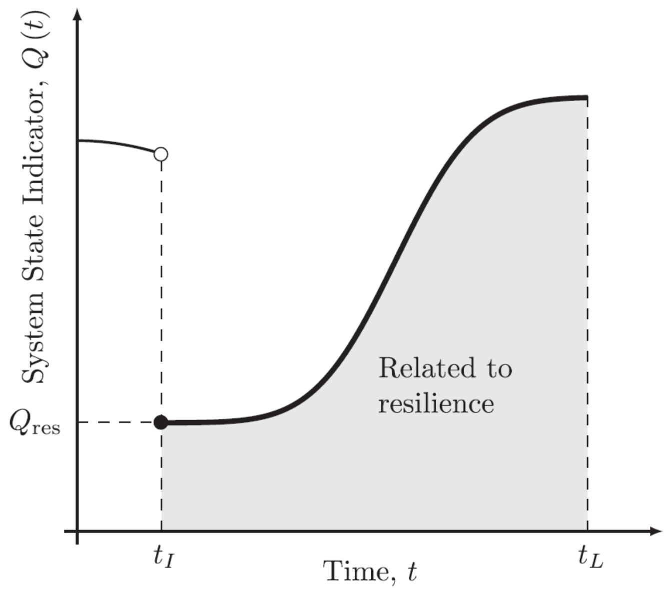


FIGURE 2.5: *A typical recovery curve used to quantify resilience [27].*

The resilience metric is defined as

$$R = \frac{\int_{t_I}^{t_L} Q(t)dt}{T_R} = \frac{\int_0^{T_R} \breve{Q}(\tau)d\tau}{T_R}, \tag{2.1}$$

where $\tau = t - t_I$ and $\breve{Q}(\tau) = Q(t - t_I)$. However, R is limited as it may give the same value of resilience for different combinations of $\breve{Q}(\tau)$ and T_R, since the area under different shaped curves may be the same, as illustrated in Figure 2.6.

To distinguish the resilience associated between recovery curves with different T_R's, t_L is replaced with a fixed time horizon t_H in (2.1), and the resilience metric is denoted as $R(t_H)$, as illustrated in Table 2.5. While the value of $R(t_H)$ for a given system and a fixed t_I may change with t_H, the ability of the system to recover, will remain unchanged [27].

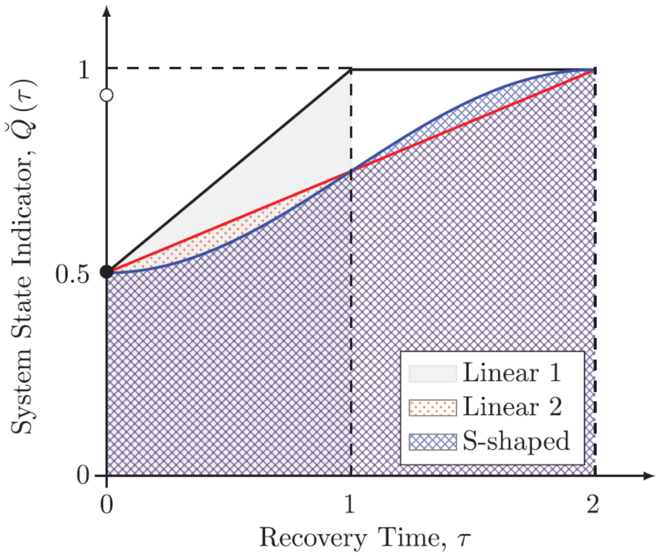


FIGURE 2.6: *The R resilience metric cannot differentiate the resilience associated with the three different recovery curves [27].*

Description	T_R	Recovery function	R	$R(t_H = 2)$	$R(t_H = 3)$
Linear 1	1	$0.5 + 0.5\ t$ $t = \{0, 1\}$	0.75	0.87	0.92
Linear 2	2	$0.5 + 0.25\ t$ $t = \{1, 2\}$	0.75	0.75	0.83
S-shaped	2	$0.75 - 0.25\ \cos(\pi \frac{t}{2})$	0.75	0.75	0.83

TABLE 2.5: *The mathematical expressions of three different recovery curves shown in Figure 2.6, and the associated resilience metric R [27].*

Partial descriptors of $\breve{Q}(\tau)$ (central measures of resilience) quantify the resilience associated with a given recovery curve. The recovery curve $\breve{Q}(\tau)$, or the Cumulative Resilience Function (CRF), represents the overall recovery progress by time τ.

Once $\breve{Q}(\tau)$ is specified, the instantaneous rate of the recovery progress is obtained. When the CRF is a continuous function of time, the instantaneous rate of recovery progress is the time derivative of the CRF [27].

The Resilience Density Function (RDF) is defined as $q(\tau) = d\breve{Q}/d\tau$ for all $\tau \in [0, T_R]$. The RDF is undefined at a possible finite set of points where the derivative of the CRF does not exist [27]. The recovery progress over any time interval $(\tau_u, \tau_v] \subseteq [0, T_R]$ is obtained by

$$\breve{Q}\left(\tau_u < \tau \leq \tau_v\right) = \int_{\tau_u}^{\tau_v} q(\tau)d\tau. \tag{2.2}$$

The CRF or the RDF of a system (analogous to the Cumulative Distribution Function (CDF) and the Probability Density Function (PDF) of random variables in probability theory) provides information about its state immediately after a shock as well as recovery, thus its' resilience.

The Center of Resilience, ρ_Q, is defined as

$$\rho_Q = \frac{\int_0^{T_R} \tau q(\tau) d\tau}{\int_0^{T_R} q(\tau) d\tau}. \tag{2.3}$$

The Resilience Bandwidth, χ_Q, a single measure to capture the dispersion, is defined as

$$\chi_Q^2 = \frac{\int_0^{T_R} (\tau - \rho_Q)^2 q(\tau) d\tau}{\int_0^{T_R} q(\tau) d\tau}. \tag{2.4}$$

Low values of χ_Q indicate that a large percentage of recovery is completed over a short period of time around ρ_Q, where high values indicate recovery is spread over a lengthy period of time.

The Resilience Skewness, ψ_Q, is defined as

$$\psi_Q = \frac{\int_0^{T_R} (\tau - \rho_Q)^3 q(\tau) d\tau}{\int_0^{T_R} q(\tau) d\tau}. \tag{2.5}$$

The magnitude of ψ_Q determines the degree of asymmetry of recovery with respect to ρ_Q, where the algebraic sign defines the direction of the skewness [27].

In equation (2.5), $\psi_Q = 0$ when the RDF is symmetric with respect to ρ_Q, which indicates the speed in recovery is the same before and after ρ_Q. When $\psi_Q > 0$, the RDF has a longer tail to the right of ρ_Q, which indicates recovery is slow during the interval $[0, \rho_Q]$, or first half of the recovery phase, and speeds up over the second half of the recovery phase, $(\rho_Q, T_R]$. When $\psi_Q < 0$, the RDF has a longer tail to the left of ρ_Q, which indicates recovery is quicker during the interval $[0, \rho_Q]$, or first half of the recovery phase, and slows down over the second half, $(\rho_Q, T_R]$.

Note ρ_Q, χ_Q and ψ_Q correspond to the mean, variance, and skewness of a random variable in probability theory. The above analogies hold for a non-decreasing CRF [27].

For a given recovery process, the information that R provides about resilience is captured by ρ_Q. However, ρ_Q cannot differentiate between recovery curves with the same $\breve{Q}(T_R)$ but different T_R's. Decision analysts may combine ρ_Q, χ_Q and higher order moments, to create composite resilience metrics, for example, $\rho_Q \pm \chi_Q$, when the two values are in the range $[0, T_R]$.

The distribution functions of a number of possible PDFs are defined in §2.5.3, to help illustrate how resilience metrics may be derived from corresponding RDFs, using equations (2.3) to (2.5).

2.5.3 Resilience density functions

Distributions of selected response variables may be fitted using the 'gamlss.dist' package, from the statistical programming tool, R. The package assesses distributions that can be used to model response variables in Generalised Additive Models for Location Scale and Shape [28].

Distributions in the 'gamlss.dist package' include a a gamma (GA) distribution, a generalized gamma (GG) distribution, a Weibull (WEI) distribution, Weibull 3 (WEI3) distribution, an inverse Gaussian (IG) distribution, a Box-Cox Power Exponential (BCPE) distribution and a Box-Cox Cole and Green (BCCG) distribution.

The specific distribution parameterisations used in the 'gamlss.dist' package, are further defined to help determine the resilience metrics of each distribution, using equations (2.3) to (2.5).

The parameterisation of the GA distribution, where μ is the mean and $\sigma^2\mu^2$ is the variance, is

$$f(y|\mu,\sigma) = \frac{y^{\left(1/\sigma^2-1\right)}\exp\left[-y/\left(\sigma^2\mu\right)\right]}{\left(\sigma^2\mu\right)^{\left(1/\sigma^2\right)}\Gamma\left(1/\sigma^2\right)} \quad \text{for } y>0,\ \mu>0 \text{ and } \sigma>0. \tag{2.6}$$

The parameterisation of the GG distribution, where μ is the mean, $\left(\sigma^2\right)\left(\mu^2\right)$ is the variance, and $z=(y/\mu)^\nu, \theta = 1/\left(\sigma^2|\nu|^2\right)$, is

$$f(y|\mu,\sigma,\nu) = \frac{\theta^\theta z^\theta \nu e^(-\theta z)}{(\Gamma(\theta) y)} \quad \text{for } y>0,\ \mu>0\ \sigma>0 \text{ and } -\infty<\nu<+\infty. \tag{2.7}$$

The parameterisation of the WEI distribution, where $\mu\Gamma\left(\frac{1}{\sigma}+1\right)$ is the mean and the variance is $\mu^2\left[\Gamma\left(\frac{2}{\sigma}+1\right)-\left(\Gamma\left(\frac{1}{\sigma}+1\right)\right)^2\right]$, is

$$f(y|\mu,\sigma) = \frac{\sigma y^{\sigma-1}}{\mu^\sigma}\exp\left[-\left(\frac{y}{\mu}\right)^\sigma\right] \quad \text{for } y>0,\ \mu>0 \text{ and } \sigma>0. \tag{2.8}$$

The parameterisation of the WEI3 distribution, where $\beta = \frac{\mu}{\Gamma((1/\sigma)+1)}$, μ is the mean and $\mu^2\left\{\Gamma(2/\sigma+1)/[\Gamma(1/\sigma+1)]^2-1\right\}$ is the variance, is

$$f(y|\mu,\sigma) = \frac{\sigma}{\beta}\left(\frac{y}{\beta}\right)^{\sigma-1} e^{-\left(\frac{y}{\beta}\right)^\sigma} \quad \text{for } y>0,\ \mu>0 \text{ and } \sigma>0. \tag{2.9}$$

The parameterisation of the IG distribution, where μ is the mean and $\sigma^2\mu^3$ is the variance, is

$$f(y|\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma^2 y^3}}\exp\left\{-\frac{1}{2\mu^2\sigma^2 y}(y-\mu)^2\right\} \quad \text{for } y>0,\ \mu>0 \text{ and } \sigma>0. \tag{2.10}$$

The parameterisation of the BCPE distribution, where μ is the median and σ is the coefficient of variation, and where $c=\left[2^{(-2/\tau)}\Gamma(1/\tau)/\Gamma(3/\tau)\right]^{0.5}$, is

$$f(y|\mu,\sigma,\nu,\tau) = \frac{y^{\nu-1}\tau\exp\left[-\frac{1}{2}\left|\frac{z}{c}\right|^\tau\right]}{\mu^\nu\sigma c 2^{(1+1/\tau)}\Gamma\left(\frac{1}{\tau}\right)} \quad \text{for } y>0,\ \mu>0,\ \sigma>0,\ \nu=(-\infty,+\infty) \text{ and } \tau>0 \tag{2.11}$$

where if $\nu\neq 0$ then $z=\left[(y/\mu)^\nu-1\right]/(\nu\sigma)$ else $z=\log(y/\mu)/\sigma$.

The parameterisation of the BCCG distribution, where μ is the median and σ is the coefficient of variation, and where ν controls the skewness, is

$$f(y|\mu,\sigma,\nu) = \frac{1}{\sqrt{2\pi}\sigma}\frac{y^{\nu-1}}{\mu^\nu}\exp\left(-\frac{z^2}{2}\right) \tag{2.12}$$

where if $\nu\neq 0$ then $z=\left[(y/\mu)^\nu-1\right]/(\nu\sigma)$ else $z=\log(y/\mu)/\sigma$, for $y>0, \mu>0, \sigma>0$ and $\nu=(-\infty,+\infty)$.

2.6 Identified research gaps

Previous food security and resilience to food insecurity analyses, as described in §2.1, are often comprehensive and consider a wide range of interacting variables, thus are difficult to conduct frequently, such as on a monthly basis. National scale food security analyses, for example the IPC and CFSVA, are difficult to conduct monthly due to intensive data collection requirements and lengthy data processing, thus hinders seasonal food security analysis.

A systems analysis approach to modelling resilience to food insecurity applies the trends of a single selected state variable, and quantifies resilience metrics using probability theory techniques [27].

The methodology proposed in this study to quantify a populations' resilience to food insecurity, as described in Chapter 3, applies a composite food security metric, particularly the FCS, as defined in §2.1.1. The FCS may be calculated from data collected through electronic questionnaires using mobile technology, thus may be collected more frequently and at a wider scale, than previous resilience to food insecurity analyses, which is suitable for resilience analysis concerned with time series data.

The FCS is used as a system state variable for resilience analysis, while previous food security analyses are used to validate the model findings. Malawi is used as a case study as the FCS has already been collected nation wide, and since there are many previous food security analyses to compare study results with. Changes in the FCS are estimated to quantify resilience to food insecurity, in terms of selected resilience metrics, as defined in equations (2.3) to (2.5).

CHAPTER 3

Methodology

"To share and use data from multiple institutions, data must be built upon common words (data elements and terminology), structures and organisation. In the world of information technology (IT), this requirement is called interoperability."

- W. Ed Hammond, *distinguished leader in the field of health informatics [24]*

Contents

The methodology used to model resilience to food insecurity follows a systems analysis approach, as resilience analysis concerns the change in a system state variable. Previous resilience to food insecurity models generally use a wide range of data, as summarised in Table A.4, collected at discrete points in time, to provide a posterior account of a populations' food insecurity. The proposed resilience to food insecurity model uses the trend of a composite food security metric: the Food Consumption Score (FCS), to evaluate a populations' ability to recover from a shock, as described in §3.1.1. The FCS may be collected using mobile technology, across a range of contexts, which not only increases the possible frequency of data collection, but also increases the scale, which is suitable for resilience analysis.

A FCS simulation model, as described in §3.1.2, is used to estimate selected population groups' change in FCS, following a shock and subject to the amount of food aid available. Simulated scenarios in which the amount of food aid available is varied for each group, are used to rank selected groups' in terms of their quantified resilience to food insecurity, as described in §3.1.3.

3.1 Modelling resilience to food insecurity

To quantify a populations' resilience to food insecurity, three processes are followed, as outlined in Figure 3.1. The first process covers data collection, as described in §3.1.1, while the second covers data modelling, as described in §3.1.2, and the third, data analysis, as described in §3.1.3.

Survey data that captures a populations' FCS, collected in Step 1(a), is used to initialise a FCS simulation model. Test scenarios, in which the amount of food aid available for each group varies, are set in Step 2(a). The FCS simulation model, in Step 2(b), simulates selected groups' likely change in FCS, following a shock. Simulated FCS trends, outputted in Step 2(c), are used in Step 3(a), to determine each groups' FCS distribution. The FCS Probability Density Functions (PDFs) from each scenario, are integrated in Step 3(b), to derive resilience metrics, outputted in Step 3(c). The quantified resilience metrics may be used to rank the groups in Step 3(d), in terms of their recovery capacity, or resilience to food insecurity, in order to determine a suitable amount of food aid to improve the chances of recovery.

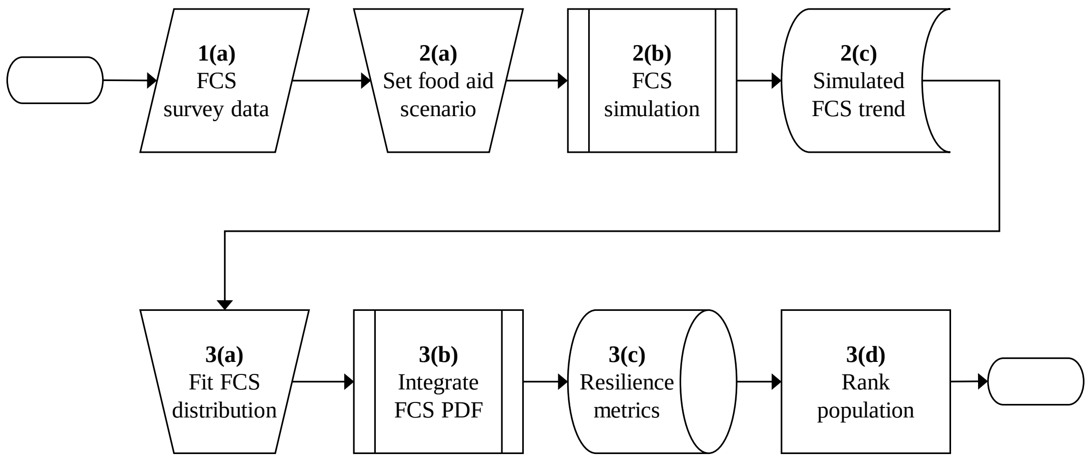


FIGURE 3.1: *Process overview diagram describing the proposed methodology for modelling resilience to food insecurity.*

Step 2 enables decision analysts to simulate different food aid scenarios using NetLogo to assess food aid decisions, however to analyse resilience to food insecurity, Step 2 is not strictly necessary, as outlined in Figure 3.2. The NetLogo model is used as a food aid decision tool, where analysts may monitor selected variables at an individual level.

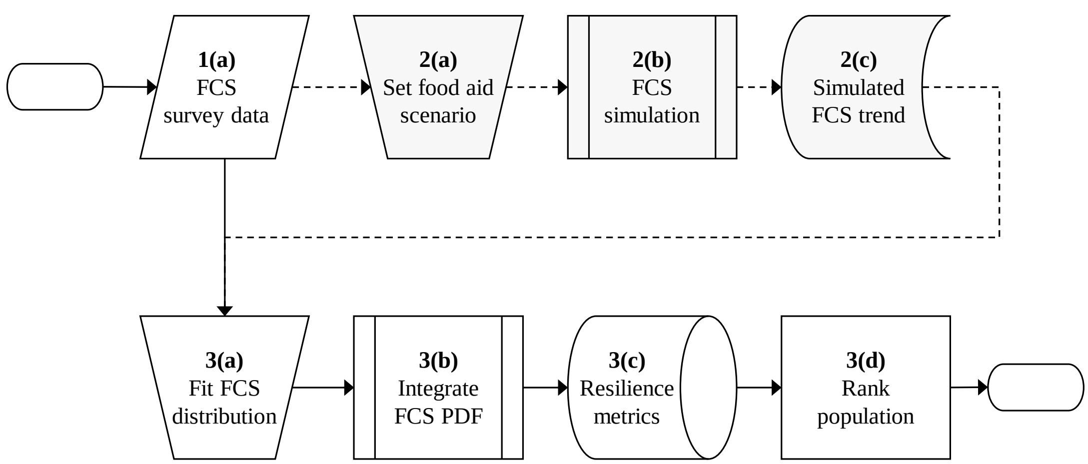


FIGURE 3.2: *Alternative process overview diagram describing the proposed methodology for modelling resilience to food insecurity, which omits Step 2, required for scenario analysis.*

Since there is no interaction between the individual people, and there are no feedback loops, the alternative resilience to food insecurity analysis model, as outlined in Figure 3.2, may simply be modelled directly in the statistical programming tool, R. Distributions may be fitted to observation variables, in this case the FCS, collected continuously over time.

3.1.1 Food security survey data

The FCS, introduced in §2.4.1, reflects a households' current food security situation and is considered to be the result of a range livelihood assets, including income, assets such as land and livestock, and access to food, basic services and social protection. The FCS may be collected using mobile technology, thus data may be collected frequently, for example on a monthly basis, and at a wide scale across a range of contexts, for example in different countries. The FCS is suitable for resilience to food insecurity analysis, as it concerns the change in a selected food security state variable over time.

The FCS, collected in Step 1(a), is captured by asking how many days in the past seven days did one eat food from the defined food groups, as illustrated in Appendix B.1. Other questions, such as what district a respondent lives in, enables data to be disaggregated by other attributes. A population may then be grouped by selected attributes, such as the district they reside in, for example. The FCS responses, are stored to a comma separated values (.csv) file, disaggregated by selected attributes, as demonstrated in Appendix D.1.

The FCS simulation model, described in §3.1.2, and the resilience to food insecurity analysis, described in §3.1.3, groups the population based on the region they live in.

3.1.2 Modelling food security

To quantify a populations' resilience to food insecurity, their FCS trend, following a shock, and subject to the monthly food aid available per household, set in Step 2(a), is simulated in Step 2(b). The FCS simulation model borrows techniques from individual-based modelling (IBM), where the simulation consists of individual agents, in this case households, that are governed by update rules, or in this case the receipt of food aid rules.

The FCS simulation model, detailed in Appendix C.1, is developed using the simulation software, NetLogo, an open source programming language and integrated development environment (IDE) suitable for IBM. The attributes of the households in the model, such as their likely FCS each month and their home region, are sampled from the data file of FCS survey responses, collected in Step 1(a), to initialise the FCS simulation model and to run food aid scenario experiments.

The FCS simulation model is described following an Overview, Design concepts, and Details (ODD) protocol, first introduced by Grimm et al [15], as it captures the stochasticity in IBM, and allows for models from different domains to be independently replicated. The ODD protocol covers the model purpose, state variables, process overview, design concepts and input data.

One of the advantages of following an IBM approach, includes the ability to model real-time data (RTD) without the need to refit distributions when sampling data. In addition, decision analysts may adjust the disaggregation groups, according to their own desired analysis objectives, as the data in the model is at an individual level and has not been aggregated at fixed levels.

Purpose

The FCS simulation model is used to estimate a populations' change in FCS, following a shock and subject to food aid. The estimated FCS trends are then used to quantify selected groups' resilience to food security and ultimately, to rank them in terms of their recovery capacity.

In addition, it may be used to investigate the question: what is the minimum amount of monthly food aid, in terms of the increase in FCS, required per household, for a populations' FCS to recover from a shock?

Entities, state variables and scales

The FCS simulation model consists of two key components: households and the landscape they are on. The households represent survey respondents, while the landscape is used to display the food security situation in selected regions. The landscape is also used to determine the amount of food aid that is available per household in each region.

SPATIAL AND TEMPORAL SCALES. The landscape is a grid of cells that each represent a defined area. The grid cells are uniform in shape and size, where the area each grid cell represents, may be varied in the model interface. The model results in this case are sensitive to the size of the grid cells, where increasing the cell size decreases the number of grid cells, thus limits the number of communities that may be modelled.

A simulation consists of t_H total time steps, in this case t_D days, grouped by t_M month, of t_{ML} month length, as outlined in Table 3.1. A shock is simulated with a predetermined occurrence at time t_I. Selecting an early shock occurrence, at $t_I = 1$ for example, allows for more simulation time for recovery, a crucial concept of resilience analysis.

A shock is covariant, where it impacts every household with a mean decrease in FCS of μ per household and a standard deviation of σ. The impact of the shock is thus stochastic and different for each household. The shock only occurs once during the simulation. Scenarios where prolonged or multiple shocks occur over a longer simulation time t_H, may be tested in future research.

Variable	Abbreviation
Simulation duration	t_H
Shock occurrence	t_I
Day	t_D
Month	t_M
Length of month	t_{ML}

TABLE 3.1: *Spatial and temporal variables.*

GRID CELLS. Grid cells may be grouped into a number of regions, with a grid cell variable R_i, as outlined in Table 3.2, indicating to which region a grid cell belongs to. A polygon shapefile is used to display the regional boundaries as well to group the grid cells. The grid cells are used to visualise the changes in household food security data over the simulation, as illustrated in Appendix C.1, which may help to quickly assess the impact of adjusting model parameters.

The model is initialised with N number of households on the grid of cells, each placed according to the population density of the defined regions. For example, the second administrative level boundaries, or regional boundaries, may be used to group the population into regions.

State variable	Abbreviation	Value(s)
Region	R_i	$\{1, 2..., p\}$

TABLE 3.2: *Grid cell state variables.*

HOUSEHOLDS. Each household is initialised with a likely monthly FCS for every month t_M, sampled from survey data, based on the region R_i that they are in. Each time step, in this case each day t_D, a households' FCS is updated according to their daily change in FCS, Δfcs_{t_D}, defined as

$$\Delta\text{fcs}_{t_D} = \frac{\Delta\text{fcs}_{t_M}}{t_{ML}}, \tag{3.1}$$

where Δfcs_{t_M} is their monthly change in FCS, defined as

$$\Delta\text{fcs}_{t_M} = \text{fcs}_{t_M+1} - \text{fcs}_{t_M}. \tag{3.2}$$

A shock decreases a households' FCS with a mean decrease of μ and a standard deviation of σ.

If a households' FCS, is less than an acceptable level of 42, and their monthly change in FCS, Δfcs_{t_M}, is negative, that household is considered to still be recovering, and will receive food aid. If a households' FCS, is greater than or equal to the acceptable level of 42, or if their likely monthly change in FCS, Δfcs_{t_M}, is positive, that household is considered to have fully recovered, or to have not been impacted, and will not receive a monthly food aid. If a households' monthly change in FCS is constant, $\Delta\text{fcs}_{t_M} = 0$, and their FCS is at an acceptable level of 42, that household is considered to have recovered and will not receive food aid. Households that are considered to be fully recovered have a recovery status of 1, where households still recovering have a recovery status of 0, as outlined in Table 3.4.

The thresholds used to determine whether a household has fully recovered from a shock, or is still recovering, are derived from the three standard FCS category thresholds defined by the World Food Programme (WFP) [33], namely; acceptable, borderline and poor, and this corresponds to damage level thresholds discussed in §2.5.2, as outlined in Table 3.3.

Food aid increases a households' FCS each time step by an amount of $\Delta\text{aid}_{t_{Di}}$ for t_{ML} time steps, based on the i region they live in, by a predefined amount selected before the model run, defined as

$$\Delta\text{aid}_{t_{Di}} = \frac{\text{aid}_{t_{Mi}}}{t_{ML}}. \tag{3.3}$$

Damage level	Reliability-based definition	Recovery	FCS-based definition
None (N)	Reliability does not change with respect to the original reliability ($\beta_0 \leq \beta$).		
Insignificant (I)	Reliability decreases but remains above the acceptable threshold ($\beta_{\text{acc}} \leq \beta < \beta_0$).	Acceptable (A)	FCS decreases but remains above the acceptable threshold ($42 \leq$ FCS).
Moderate (M)	Reliability decreases below the acceptable threshold but remains above a minimum tolerable threshold ($\beta_{\text{tol}} \leq \beta < \beta_{\text{acc}}$).	Borderline (B)	FCS decreases below the acceptable threshold but remains above a minimum tolerable threshold ($13 \leq$ FCS < 42).
Heavy (H)	Reliability decreases below a minimum tolerable threshold ($\beta < \beta_{\text{tol}}$).	Poor (P)	FCS decreases below a minimum tolerable threshold (FCS < 13).

TABLE 3.3: *Reliability-based and Food Consumption Score recovery based definitions.*

A households' FCS ranges from 0 to 112, where if a household consumed every food group everyday of the week, 112 is the maximum total score. The monthly increase in FCS from food aid ranges from 0 to 12, as outlined in Table 3.4, as any amount larger than 12 results in similar levels of recovery.

State variable	Abbreviation	Value(s)
Monthly food consumption score	fcs_{t_M}	$\{0, 1..., 112\}$
Monthly food aid received	$\text{aid}_{t_{Mi}}$	$\{0, 1..., 12\}$
Region	R_i	$\{1, 2..., p\}$
Recovery status	rec	$\{0, 1\}$

TABLE 3.4: *Household state variables.*

Process overview and scheduling

The process overview pseudo-code of the FCS simulation model, as outlined in Algorithm 1, is shown to provide an indication of how a populations' FCS, following a shock, is estimated.

Line 1 in Algorithm 1 initialises the model by loading the required data, disaggregated by month and region, as outlined in Appendix D.1.

Line 2 sets up the simulation model, and specifies how much food aid is available in each region and how many households are placed in each region, according to the selected model parameters and input data. In particular, the model is set by placing N households on a landscape, according to the selected population density. Each household is assigned a FCS, based on their location, according to survey response data. The amount of monthly food aid available per household in each region may be set in an experiment tool or on the interface before each simulation run.

Line 3 runs the model and is the start of each iteration in the simulation. Lines 4 and 5 terminate the simulation if the simulation duration reaches t_H.

Lines 6 and 7 concern the simulated shock, where the shock occurrence t_I is predetermined. The impact of the shock on all households' FCS, in line 7, is random with a mean decrease of μ and standard deviation of σ.

Line 8 assesses whether a persons FCS is above the acceptable level of 42 or whether their monthly change in FCS is not negative and line 9 assigns a 1 to their recovery status if either of the conditions are met. Line 11 assigns a 0 to a persons recovery status is neither of the conditions are met, indicating that the person has not recovered.

Line 12 updates each households' FCS according to their expected daily change in FCS.

Line 13 and 14 determine whether a household may receive food aid, where line 13 checks if their recovery status is 0 and line 142 increases their FCS by a predetermined amount, based on the region they live in.

The minimum FCS a household can have is 0, set in lines 15 and 16 and the maximum is 112, set in lines 17 and 18.

Lastly, the process is iterated back to line 3 in line 19, t_H times, specified in line 4.

Algorithm 1: Process overview pseudo-code of the food security simulation model

1 **load data**
2 **set up**
3 **go**
4 **if** $time = t_H$ **then**
5   **stop**
6 **if** $time = t_I$ **then**
7   fcs $\leftarrow$ fcs $-$ a random number $X \sim N(\mu, \sigma)$
8 **if** $fcs \geq 42$ ***or*** $(fcs_{t_M+1} - fcs_{t_M}) \geq 0$ **then**
9   rec $\leftarrow 1$
10 **else**
11   rec $\leftarrow 0$
12   fcs $\leftarrow$ fcs $+ (\text{fcs}_{t_M+1} - \text{fcs}_{t_M})/t_{ML}$
13   **if** $rec = 0$ **then**
14   fcs $\leftarrow$ fcs $+ \text{aid}_{t_{Mi}}/t_{ML}$
15   **if** $fcs \leq 0$ **then**
16   fcs $\leftarrow 0$
17   **if** $fcs > 112$ **then**
18   fcs $\leftarrow 112$
19 go to line 3

A detailed account of the simulation model developed in NetLogo, is provided in Appendix C.2.

Design concepts

The model is used to simulate the impact of shocks and food aid on a populations' FCS trend, to analyse their resilience to food insecurity. The FCS simulation model, unlike an IBM, does not concern interaction and the emergent behaviour. The applicable design concepts described, capture model stochasticity, where the concepts which do not apply have been omitted.

BASIC PRINCIPLES. The primary motivation for the FCS simulation model is to estimate a populations' change in FCS, following a shock and subject to food aid, using mobile survey data. The estimated FCS trends are used to investigate the impact of food aid following a shock, and to rank selected groups' in terms of their quantified resilience to food insecurity, or recovery capacity.

STOCHASTICITY. Shocks are covariant, thus every household in all regions are impacted with a normally distributed mean decrease in a households' FCS of μ, and a standard deviation of σ. Idiosyncratic shocks that impact smaller groups of households, or shocks that impact certain regions more than others, may be considered in future research.

OBSERVATION. Each time step, the FCS distribution of selected population groups is stored to a .csv file, to be used for further resilience analysis. The FCS distributions and FCS trends, are reported to the model interface, as illustrated in Appendix C.1.

Initialisation and input data

The model is initialised with N households, placed on the landscape according to the population density. The landscape is read from a polygon shapefile, for example a second administrative level, or regional, boundaries shapefile. The region in which households are placed is their home region and does not change. Each household is initialised with a monthly FCS, based on their home region, sampled from a survey data file. The attributes of households, particularly their FCS each month, is read from a .csv data file, disaggregated by month and region.

The model samples N households from a data file of survey respondents, where the attributes assigned to each household in the model, such as their monthly FCS, are based on selected attributes, such as their region, in the survey responses. Responses are sampled directly from a data file to facilitate real-time monitoring, by allowing for additional survey responses to be continuously included, without the need to adjust model parameters based on an updated distribution. Sampling the attributes of households from granular data, such as individual responses, allows decision makers to disaggregate the data by different selected variables, in a range of orders, where the input data for the model would simply require restructuring, rather than refitting distributions and adjusting model parameters. The model samples N random responses from the same data file, K number of iterations, to account for the probability of likely responses, where K may be increased to improve data representation.

Sampling responses, rather than forecasting responses, does limit the simulation duration t_H, however, since the model concerns quantifying a groups' resilience to food insecurity, rather than predicting their FCS trend, experiments are based on actual data, rather than forecasted data.

The level of food aid (between the selected interval 0 and 12) available per household each month, for each region, is set before each simulation run. These scenario parameters are used to determine a suitable amount of food aid required to ensure a population recovers from a shock.

Each simulation consists of K repetitions, where the average of the results of all the repetitions, is considered for further resilience to food insecurity analysis. The results are outputted to a

.csv file to be read into R for distribution fitting, as described in §3.1.3.

3.1.3 Resilience to food insecurity metrics

The simulated FCS trends outputted in Step 2(c), are used to quantify selected groups' resilience to food insecurity in Step 3. The FCS distributions are fitted in Step 3(a), where the derived PDFs are integrated in Step 3(b), to quantify resilience metrics, outputted in Step 3(c), and ultimately rank a population in Step 3(d), in terms of their resilience to food insecurity.

The FCS distributions may be fitted in Step 3(a), using the 'gamlss.dist' package [28], from the statistical programming tool, R, as illustrated in Appendix E.1. Once the FCS distribution of each group is fitted and their FCS PDF is defined, resilience metrics are derived in Step 3(c), using equations (2.3) to (2.5). The gamlss.dist package tests for an range of distributions, and recommends the distribution with the best fit according a number of measures.

The defined equations essentially integrate a groups' FCS trend, to quantify their change in FCS over time, or FCS recovery, following a shock. In particular, derived resilience metrics are used to describe the duration or chance of recovery, the spread of the recovery progress and the pace of recovery, of selected groups' FCS. The resilience metrics, outputted in Step 3(d), may be used to rank groups, in terms of their recovery capacity, or resilience to food insecurity.

The Center of Resilience, ρ_Q, as defined in equation (2.3), captures the duration of recovery and indicates the chance of recovery. The Resilience Bandwidth, χ_Q, as defined in equation (2.4) captures the dispersion, or spread of recovery. The Resilience Skewness, ψ_Q, as defined in equation (2.5), captures the degree of asymmetry of recovery with respect to ρ_Q, or pace of recovery, where the algebraic sign defines the direction of the skewness [27].

Selected groups may be ranked in terms of selected resilience metrics, as outlined in Table 3.5.

Symbol	Indicator	Description	Interpretation
ρ_Q	Centre of resilience	The duration or chance of recovery.	High values indicate a short recovery duration or high chance of recovery.
χ_Q	Resilience bandwidth	The dispersion of recovery in relation to ρ_Q.	Lower values indicate progress in recovery is less dispersed around ρ_Q.
ψ_Q	Resilience skewness	The pace of recovery.	A positive values indicate recovery is slower during the first half of the recovery phase than the second half. Low absolute values indicate a steady pace in recovery.

TABLE 3.5: *Descriptive comparison of the resilience metrics.*

Primarily, groups may be ranked in terms of their chance of recovery, where higher values of ρ_Q indicate a higher chance of recovery. Groups may then be ranked in terms of the dispersion of their recovery progress, where higher values of χ_Q indicate recovery is more spread over time. Groups may thirdly be ranked by the pace of their recovery, where high magnitude of ψ_Q indicates a fluctuating pace of recovery thus the need for varying amounts of food aid.

Groups may also be ranked using a combination of the metrics, depending on the intention of food aid intervention, for example, to speed up recovery initially, focus should be placed on χ_Q, where to sustain food aid over time, focus should be placed on ψ_Q.

The recovery duration is most suitable for ranking groups, as it describes the chance of recovery, where higher values of ρ_Q indicate a higher chance of recovery. Groups with lower values of ρ_Q should be prioritised consistently for food aid, as they have a lower chance of recovery.

The dispersion of the recovery progress is suitable for ranking groups when concerned with sustaining food aid over time. Higher values of χ_Q indicate recovery is dispersed or spread over time, thus a stable amount of food aid is required, where lower values indicate most of recovery happens over a short period of time, thus varying amounts of food aid are required [27].

The magnitude of ψ_Q corresponds to the pace of recovery, and indicates the degree of asymmetry of recovery in relation to ρ_Q, were the algebraic sign indicates the direction of skewness. The pace of recovery is suitable for ranking groups when concerned with when food aid is required. Low values of ψ_Q, indicate a steady pace of recovery, where high values indicate the pace of recovery is faster in either the first or second phase of the recovery process. Negative values of ψ_Q indicate the progress in recovery is quicker before ρ_Q than after, where positive values indicate the progress in recovery is slower before ρ_Q than after [27].

The resilience metrics from Step 3, derived from the simulated FCS trends in Step 2, using mobile individual food security data collected in Step 1, may be used to rank a population in terms of their recovery capacity, as demonstrated by the Malawi case study in Chapter 4.

CHAPTER 4

Data and Results for Malawi

"mVAM endeavours to make the data collected by the project 'open' and accessible to people everywhere."

- mVAM, *mobile Vulnerability Analysis and Mapping [33]*

Contents

A composite food security metric: the Food Consumption Score (FCS), collected in Malawi using mobile technology, is used to model household food security, as described in §4.1.1. A FCS simulation model is used to estimate the change in FCS of selected population groups, following a shock and subject to food aid, where groups are based on the region a household is located in, as described in §4.1.2. Simulated scenarios are used to rank the three regions in Malawi, in terms of their quantified resilience to food insecurity, as described in §4.1.3.

4.1 Resilience to food insecurity: A Malawi case study

To model a populations' food security using mobile survey data, Malawi is used as a case study, since mobile food security survey data, specifically the FCS, has already been collected nation wide. In addition, there are pre-existing food security analyses, particularly the 2019 Integrated Food Security Phase Classification (IPC) analysis, to compare results with and verify findings.

To quantify resilience to food insecurity, three processes are followed, as outlined in Figure 3.1. The first process covers data collection, specifically mobile FCS survey data from Malawi, as described in §4.1.1. The second process covers data modelling, specifically simulating regional FCS trends, as described in §4.1.2. The third process covers data analysis, specifically resilience to food insecurity analysis, as described in §4.1.3.

4.1.1 Malawi food security survey data

The World Food Programme (WFP) collects monthly food security data using mobile technology to monitor real-time food security trends. The computer-assisted telephone interview (CATI), which enables responses from illiterate respondents, is one of the remote mobile data collection methods used by WFPs' mobile Vulnerability Analysis and Mapping (mVAM) unit [33].

In February 2017, WFPs' mVAM unit started conducting national monthly household food security surveys in Malawi, using CATI, as outlined in Appendix B.1. Different respondents were selected from a national database of mobile subscribers each month, thus the survey data is cross-sectional, and not longitudinal. The CATI surveys concluded in May 2017, with 5 507 responses collected. The survey includes two questions that capture a respondents' FCS and the region that they live in, required in Step 1(a), to disaggregate the FCS simulation model input data.

Other questions, such as whether they received assistance, allows for the data to be disaggregated by other attributes, for example, by beneficiary status. For demonstrative purposes and to improve data processing, this study disaggregates the data and groups the population by the regional boundaries in Malawi. Disaggregating the data by beneficiary status allows for a more accurate food aid analysis than the current food aid model, which considers a households FCS, including food aid meals.

Of the 5 507 respondents, 752 are from the Northern Region, labelled North, while 2 378 are from the Central Region, labelled Central, 2 375 are from the Southern Region, labelled South, and 2 respondents did not indicate where they are from and have been omitted from the analysis.

The mean and median FCS is highest in the Northern Region (55.3 and 54.5) and lowest in the Central Region (52.1 and 50), with the Southern Regions' mean and median (52.3 and 50.5), fairly similar to the Central Region, as shown in Figure 4.1 and Figure 4.3.

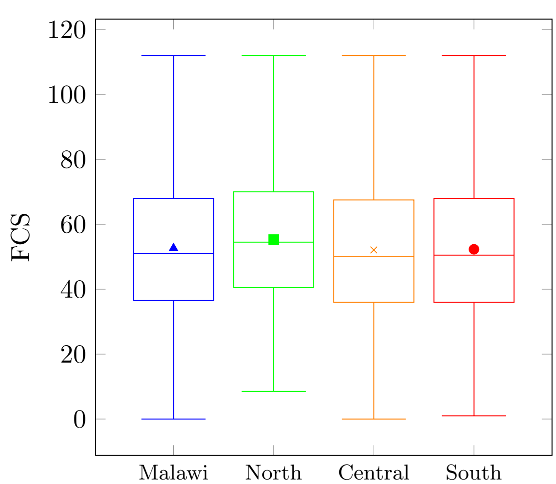


FIGURE 4.1: *Box plots showing the variation of the Food Consumption Score from February 2017 to May 2017 Malawi survey data.*

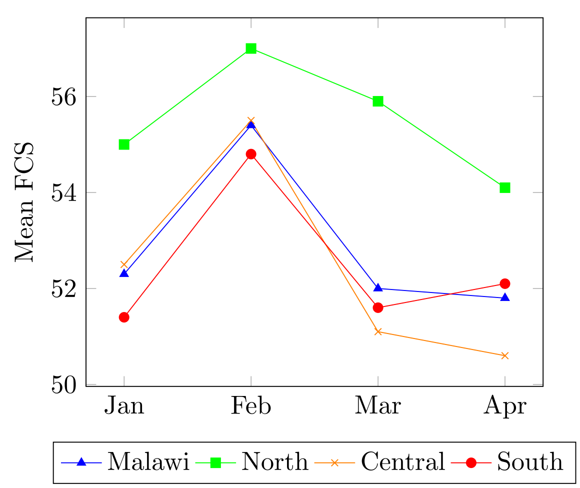
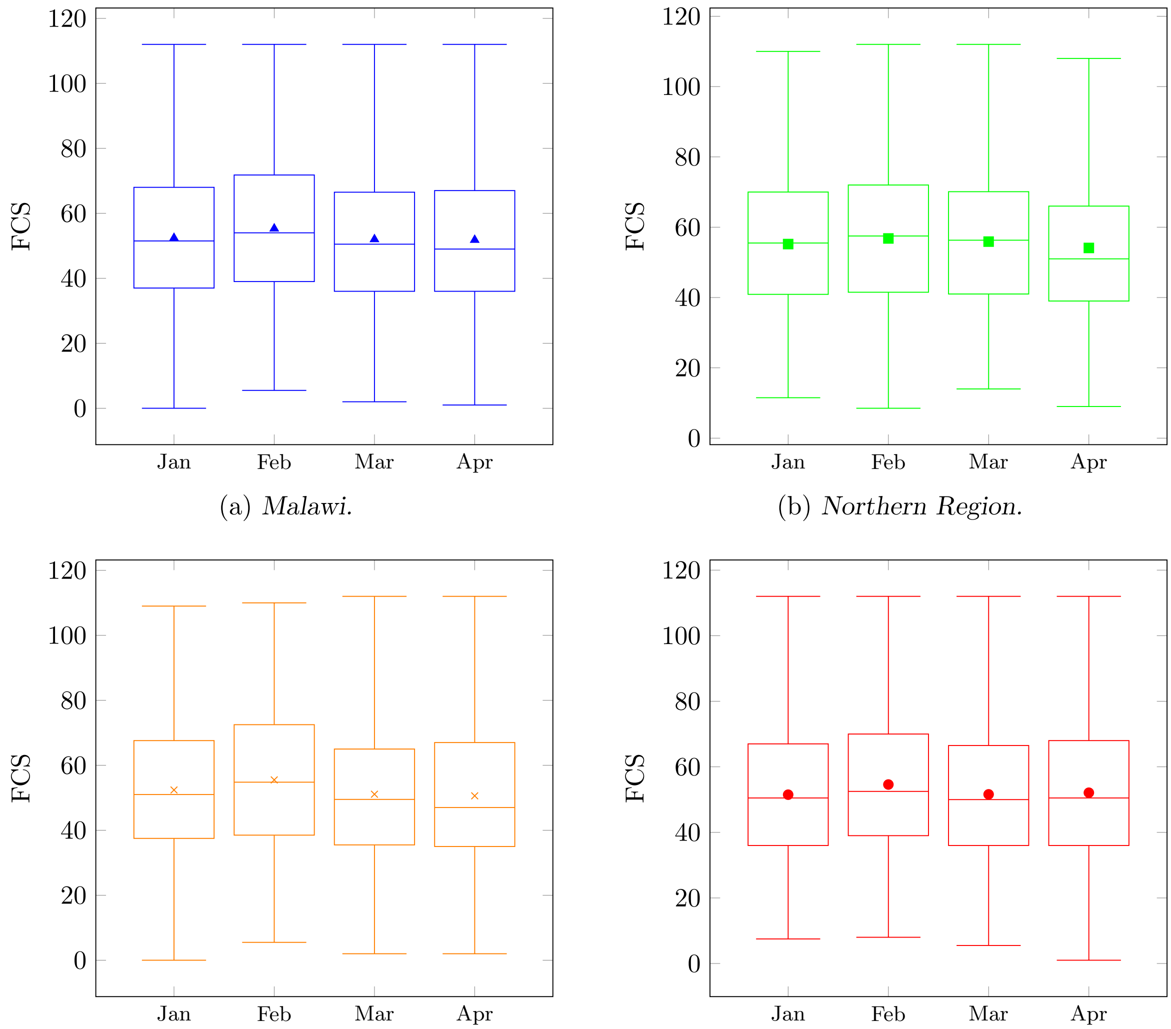


FIGURE 4.2: *Mean Food Consumption Score four month trend from February 2017 to May 2017 Malawi survey data.*



(a) *Malawi.* (b) *Northern Region.*

(c) *Central Region.* (d) *Southern Region.*

FIGURE 4.3: *Box plots showing the monthly variation of the Food Consumption Score from February 2017 to May 2017 Malawi survey data.*

Since the FCS is collected using mobile technology, there may be modal bias, where the survey responses are solely from households who own cellphones, where households with no access to a cellphone, which may be even more food insecure than households with access to a cellphone, cannot partake in the survey.

A higher FCS in the Northern Region is not unusual, as conveyed in the 2019 Integrated Food Security Phase Classification (IPC) map and shown in Figure 2.1. The mean FCS is typically lowest in the Southern Region and then the Central Region, as is the case in January and February, as shown in Figure 4.2. From March to April, the Southern Region experiences an increasing FCS trend, while the Northern Region, Central Region, and Malawi overall, experience a decreasing FCS trend.

To analyse a populations' change in FCS, the collected FCS responses in Step 1, are stored to a comma separated values (.csv) file, disaggregated by month and region, as illustrated in Appendix D.1.

4.1.2 Modelling food security in Malawi

To estimate a populations' continuous change in FCS, following a shock and subject to food aid, a FCS simulation model samples input data from a survey response .csv data file, collected in Step 1(a), as illustrated in Appendix D.1. The selected levels of food aid for each region, in terms of the monthly increase in FCS per household, are set in Step 2(a), before running the simulation in Step 2(b). The simulated household FCS trends for each region, with various levels of food aid, outputted in Step 2(c), as illustrated in Appendix D.2, are used in Step 3 for resilience to food insecurity analysis.

The FCS Probability Distribution Function (PDF) of each region is fitted in Step 3(a), as illustrated in Appendix E.1, to quantify their resilience to food insecurity in Step 3(b), as illustrated in Appendix E.2. The resilience metrics, outputted in Step 3(c), are then used in Step 3(d), to analyse and rank the regions in terms of their resilience to food insecurity, as described in §4.1.3.

The FCS simulation model, developed in NetLogo, enables multiple model experiments and the exploration of resulting parameter spaces. NetLogo is an open source modelling tool suitable for individual-based modelling. A particular NetLogo tool: BehaviourSpace, allows for parameter sweeping, by systematically varying model settings and recording the results of each run [4]. Simulating the same model with different settings, in this case the amount of monthly food aid per household that is available, in terms of the increase in FCS, may lead to different resilience metric results. Each simulation consists of $K = 100$ repetitions of each setting, where the average of the results of all 100 repetitions, is considered for further resilience to food insecurity analysis.

The second administrative level boundary, or regional boundary, shapefile of Malawi is used to initialise the FCS simulation model and to display selected variables on the model interface. The model is initialised with $N = 500$ households, that are placed on the landscape according to the regional population density, as outlined in Table 4.1.

Region	Population 2018 [6]	% of total	Survey sample size	% of total	Simulated sample	% of sample
Northern Region	2 289 780	13	752	14	65	13
Central Region	7 523 340	43	2 378	43	213	43
Southern Region	7 750 629	44	2 375	43	222	44
Malawi	17 563 749	100	5 505	100	500	100

TABLE 4.1: *Regional population and percentage of population, based on the national census, the mobile survey and the food security simulation model.*

The Northern Region accounts for the lowest portion of the total population, of 13 percent, while the Central Region and Southern Region account for fairly similar portions, of 43 and 44 percent, respectively, as outlined in Table 4.1. The 2018 population estimate is used to determine the regional population density [6], where accordingly 65 households are placed in the Northern Region, 213 in the Central Region, and 222 in the Southern Region, as outlined in Table 4.1, and shown by the respondents placed on the interface map, as illustrated in Appendix C.1.

The simulation duration is set to $t_H = 90$ time steps, in this case each representing a day, specifically the first quarter of 2017. The shock occurrence is set to $t_I = 1$, meaning the shock occurs at the beginning of January, to allow simulation time for recovery. In this case, the shock has a random impact on the entire population with a normally distributed mean change in a households' FCS of $\mu = -20$, and a standard deviation of $\sigma = 5$. The average impact of the shock does not vary over scenarios, where the decrease in FCS selected is around 20, about half of the acceptable FCS threshold of 42. The magnitude and scale of impact are both unvarying, where a shock randomly impacts all regions each scenario.

The FCS simulation model runs 343 different combinations of model settings, in terms of the amount of monthly food available per household in each region, or scenarios, defined in Step 2(a). The selected amount of monthly food aid available per household is adjusted from 0 to 12 in intervals of 2, for each region. Each simulation, in Step 2(b), completes 100 repetitions, thus the model experiment completes a total of 343 000 simulation runs.

The seven scenarios, where there is an equal amount of monthly food aid available per household in each region, are used for initial resilience analysis, to determine a suitable amount of monthly food aid per household, required for a population to recover from a shock.

The scenario where the amount of monthly food aid available per household for each region is set to 0, is used as a baseline scenario to determine how the population recovers from a shock, without food aid intervention. The simulated shock at $t_I = 1$, impacts each region fairly equally, as shown on the left in Figure 4.4, as the decreases in FCS are fairly parallel.

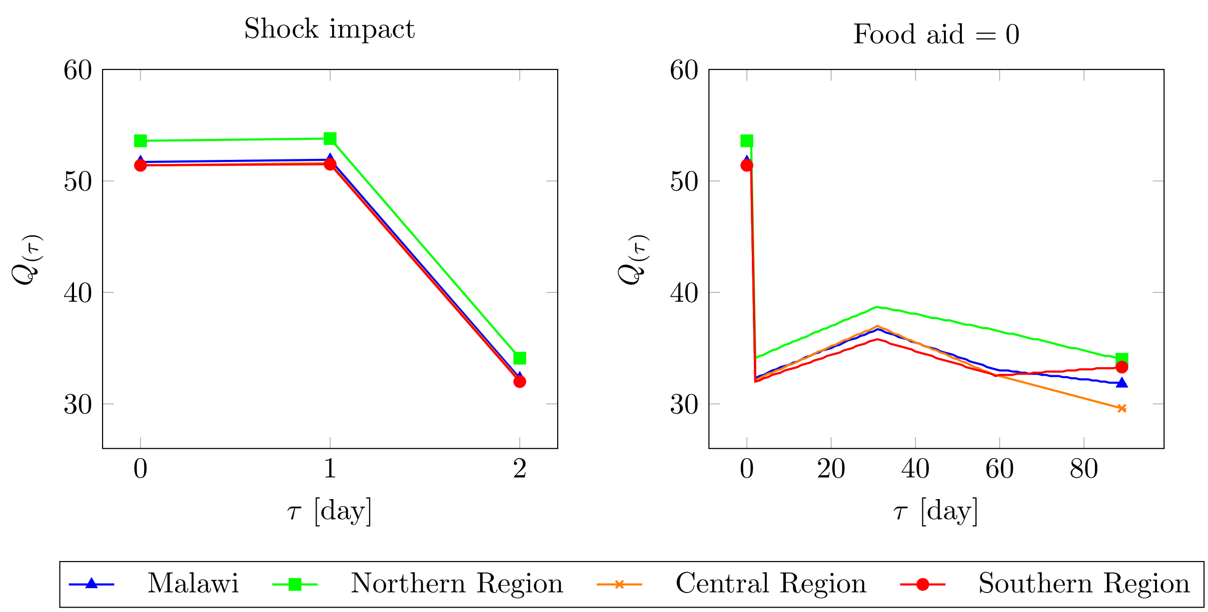


FIGURE 4.4: *Simulated Food Consumption Score trends, where there is no monthly food aid per household available, for all regions.*

The simulated FCS trends of each region, as shown on the right in Figure 4.4, correspond to that in Figure 4.2, and reveal an initial increasing trend that starts to decrease around day 31, in this case at the beginning of February, where the FCS trends in both Northern Region and Central Region continue to decrease until day 90, or the end of March. Without food aid intervention, the average FCS of each region does not recover to an acceptable level of 42. This may be due to the underlying FCS trend of the data, where the survey data is collected during a time where no significant shock occurred. To get a better understanding of resilience, actual shock data should be used.

The Northern Region is typically considered to be the most food secure of the three regions, as conveyed in the 2019 IPC report and as shown in Figure 2.1. The Northern Region is generally the most food secure region in the baseline scenario too, where the mean FCS reaches a maximum of 38.7 at the start of February, without food aid intervention, as shown on the right in Figure 4.4.

The Central Region reaches a maximum mean FCS of 37 at the start of February, while the Southern Region, which is typically considered to be the least food secure, reaches a maximum mean FCS of 35.8 at the start of February. Despite having the lowest FCS, the Southern Region is the only region where the FCS trend continues to increase from day 60, in this case at the beginning of March, where the FCS trend in the Northern Region and Central Region decreases from the start of February, as shown on the right in Figure 4.4.

Without additional food aid, the overall population struggles to recover from a shock, where the FCS trend following a shock, does not reach an acceptable level of 42, throughout the simulation duration, as shown on the right in Figure 4.4. To determine the effect of food aid on a populations' response capacity to shocks, and ultimately to quantify their resilience to food insecurity, the seven scenarios in which equals amounts of food aid available per household, in each region, are further analysed.

The simulated total food aid required over the simulation duration of 90 days, in this case representing the first three months of 2017, as outlined in Table 4.3, is calculated as

$$\text{simulated food aid required} = \sum_{i=1}^{3} \left(\text{pin}_{(i)} \times \text{aid}_{(i)} \right), \tag{4.1}$$

where $\text{pin}_{(i)}$ is the total number of simulated households in need of food aid in region R_i and $\text{aid}_{(i)}$ is the amount of food aid available per household in region i. A household is considered to be in need of food aid if their recovery status is 0.

The weighted total food aid required, as outlined in Table 4.3, is calculated as

$$\text{weighted food aid required} \approx \sum_{i=1}^{3} \left(\frac{\text{pin}_{(i)}}{\text{pop}_{(i)}} \times \text{Pop}_{(i)} \times \text{aid}_{(i)} \right), \tag{4.2}$$

where $\text{pop}_{(i)}$ is the total number of simulated households in region R_i, and $\text{Pop}_{(i)}$ is the total population in region R_i, as outlined in Table 4.1. The total population in need may be approximated to the nearest 500 000.

For example, the calculated weighted total food aid required, where food aid available per household is set to 8, is approximately 94 million, as demonstrated in Table 4.2.

Region	$\text{pin}_{(i)}$	$\text{pop}_{(i)}$	$\text{Pop}_{(i)}$	Approximate population	Food aid	Total food aid required
Northern Region	41	65	2 289 780	1 500 000	8	12 000 000
Central Region	143	213	7 523 340	5 000 000	8	40 000 000
Southern Region	150	222	7 750 629	5 300 000	8	42 400 000
Malawi	334	500	17 563 749	11 800 000	8	94 000 000

TABLE 4.2: *Weighted total food aid required calculation, where food aid is set to 8.*

To ensure 100 percent of the population recovers to an acceptable level, from a shock, in the set time horizon, a monthly food aid of 8, in terms of the increase in FCS, is required, as outlined in Table 4.3. An amount of monthly food aid greater than 12 is not considered. When the monthly food aid available per household in each region is set to 6 or 4, a large percentage of the populations' FCS recovers to an acceptable level, with 99 and 94 percent respectively, while a significantly lower weighted total food aid is required, as outlined in Table 4.3.

Monthly food aid per household (increase in FCS)	Percentage of households that recovers to FCS > 42	Estimated simulated total food aid required	Weighted total food aid required (rounded to the nearest 500 000)
0	66	0	0
2	70	668	23 500 000
4	94	1 336	47 000 000
6	99	2 004	70 500 000
8	100	2 672	94 000 000
10	100	3 341	117 500 000
12	100	4 009	141 000 000

TABLE 4.3: *Percentage of population that recovers to an acceptable level, when receiving selected amounts of monthly food aid, in terms of the increase in Food Consumption Score.*

The simulated FCS trends for each region from the seven scenarios with equal levels of food aid in each region, as shown in Figure 4.5, are used to determine the FCS distributions for each region and ultimately derive resilience to food insecurity metrics, as defined in §4.1.3.

An amount of monthly food aid available per household, greater than 8, results in 100 percent of the population FCS recovering, and is limited at 12 for analysis purposes.

Overall, the average FCS in Malawi does not recover to an acceptable threshold of 42, when the monthly food aid available is set to 2, 4 or 6, with a maximum FCS of 34.8, 37.9 and 41.1, respectively. The average FCS in Malawi reaches an acceptable average FCS threshold of 42 when food aid is set to 8, 10 or 12, with a maximum FCS of 44.4, 47.5 and 50.9, respectively.

As the amount of food aid increases, the maximum FCS for Malawi increases, and the gradient of the FCS trend evens out, indicating that availing more food aid improves the chances of recovery as well as the speed of recovery, as shown in Figure 4.5.

The overall FCS trend in Malawi has a much more gradual increase when the monthly food aid available is set to 2, than when food aid is set to 12, where the gradient in the FCS trend is steeper and more constant, as shown in Figure 4.5 and Figure 4.6.

The average FCS in the Northern Region does not recover to an acceptable threshold of 42, when the monthly food aid available is set to 2 or 4, with a maximum FCS of 37.3 and 40.5, respectively. The average FCS in the Northern Region reaches an acceptable average FCS threshold of 42 when food aid is set to 6, 8, 10 or 12, with a maximum FCS of 44, 46.84, 49.7 and 53, respectively, as shown in Figure 4.5 and Figure 4.6.

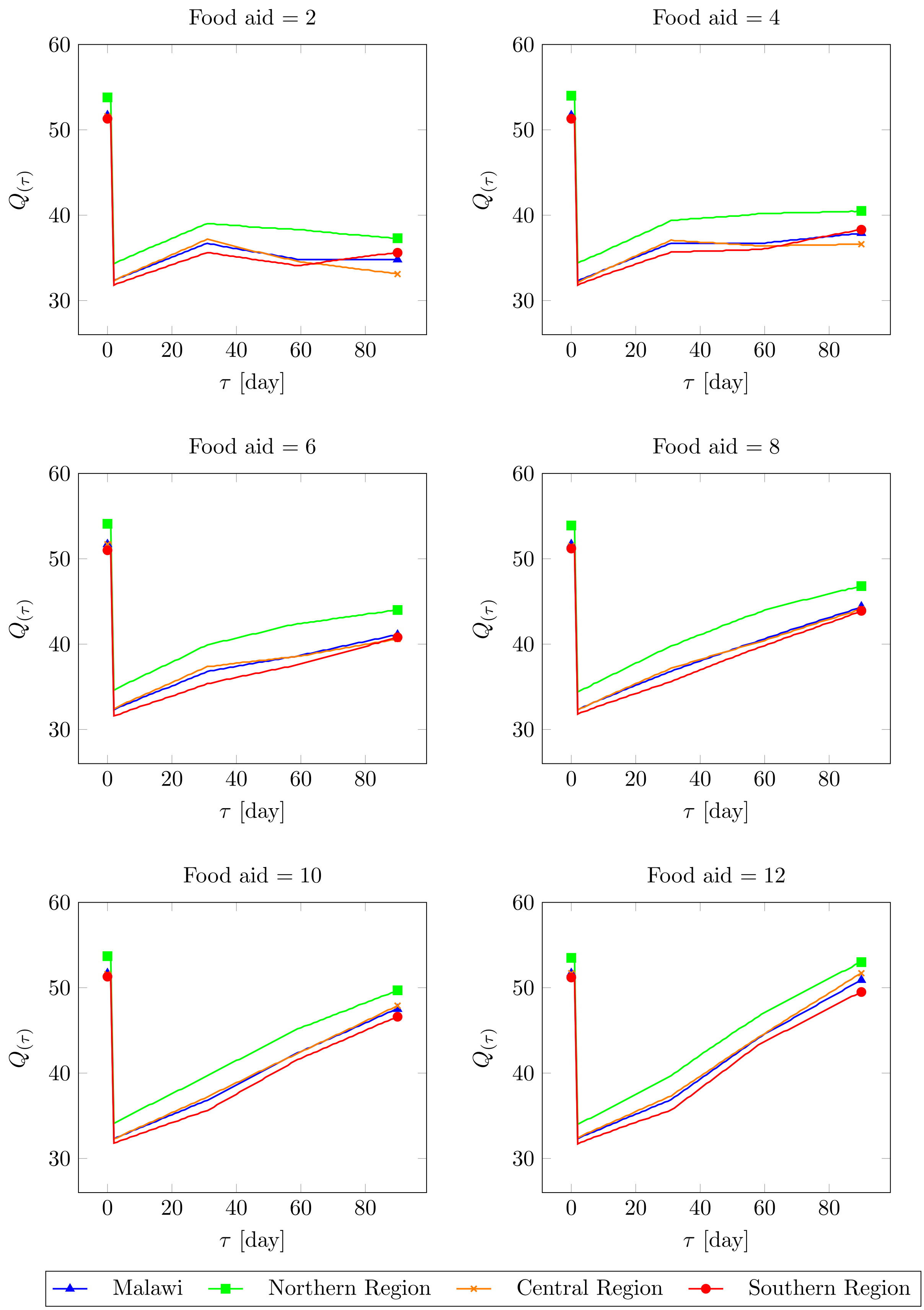


FIGURE 4.5: *Simulated Food Consumption Score trends, where different levels of monthly food aid per household are available, for all regions.*

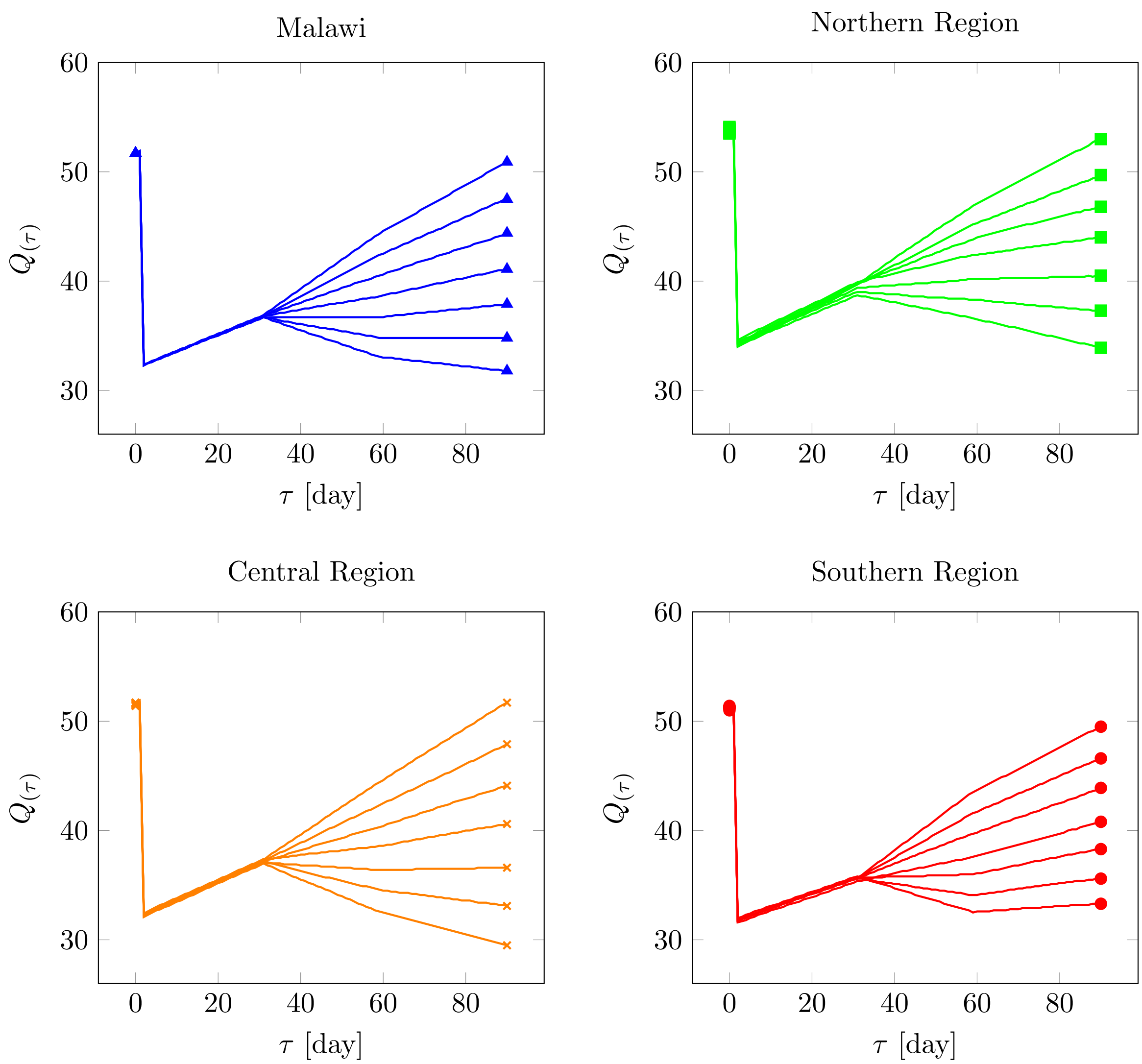


FIGURE 4.6: *Simulated regional Food Consumption Score trends, for different levels of monthly food aid available per household.*

The average FCS in the Central Region does not recover to an acceptable threshold of 42 when monthly food aid available is set to 2, 4 or 6, with a maximum FCS of 33.1, 36.6 and 40.6, respectively, but recovers to an acceptable level when food aid is set to 8, 10 or 12, with a maximum FCS of 44.1, 47.9 and 51.7, respectively, as shown in Figure 4.5 and Figure 4.6.

The average FCS in the Southern Region does not recover to an acceptable threshold of 42 when monthly food aid available is set to 2, 4 or 6, with a maximum FCS of 35.6, 38.3 and 40.8, respectively, but recovers to an acceptable level when food aid is set to 8, 10 or 12, with a maximum FCS of 43.9, 46.6 and 49.5, respectively, as shown in Figure 4.5 and Figure 4.6.

The FCS is generally the highest in the Northern Region, as shown in Figure 4.5, corresponding to the underlying FCS trend in survey data, as shown in Figure 4.2, as well as to the base case scenario, as shown in Figure 4.2. The FCS is generally the lowest in the Southern Region, as shown in Figure 4.5, indicating that the Southern Region requires more food aid than the other regions, to recover from a shock. The Southern Region is typically considered to be the more food insecure than the Central Region and Northern Region, as shown in Figure 2.1 and as conveyed in the 2019 IPC report [30].

The FCS trends in each region improve as the amount of food aid available increases, in terms of the evenness of the gradient, where the gradient is generally more even when food aid is set to 12, than when it is set lower than 12, indicating that an increase in the amount of food aid may lead to a steadier pace in recovery, as shown in Figure 4.5 and corresponding to Figure 4.6.

The FCS trends in each region improve as the amount of food aid available increases, in terms of the steepness of the gradient, where the gradient is generally steeper when food aid is set to 12, than when it is set lower than 12, indicating a higher chance of recovery, as shown in Figure 4.6.

The remaining 363 scenarios, where the amount of monthly food aid available per household, varies in each region, are used to assess whether combinations of food aid per household, may result in similar levels of recovery, in terms of percentage of the population whose FCS recovers to an acceptable level, from the simulated shock, as demonstrated in Table 4.4.

A scenario comparison may inform food aid scheduling when considering food aid funding and time constraints, by determining where food aid may be decreased, without impacting the overall percentage of the population whose FCS recovers.

Amount of monthly food aid available			Food aid required	
Northern Region	Central Region	Southern Region	Estimated simulated total	Approximate weighted total
8	8	6	2 373	83 500 000
6	8	8	2 590	91 000 00
8	10	8	2 595	104 000 000
10	10	8	3 041	107 000 000
10	8	10	3 054	107 500 000

TABLE 4.4: *Scenarios where* 100 *percent of the populations' Food Consumption Score recovers to an acceptable level from a shock, subject to varying amounts of food aid per region.*

Determining the total amount of food aid required, with varying levels of monthly food aid per household for each region, may help with selecting the most effective food aid schedule, particularly in lowering the total cost of food aid, when food aid is limited. The simulated total food aid required and weighted total food aid required, for each scenario, as outlined in Table 4.4, are calculated using equations (4.1) and (4.2), respectively.

Decreasing the amount of food aid available in certain regions may result in an equal percentage of the overall population whose FCS recovers from a shock, while significantly decreasing the total required food aid, as outlined in Table 4.4. For example when food aid is set to 8 in the Northern Region and Central Region and 6 in the Southern Region, 100 percent of the populations' FCS recovers to an acceptable level, while the simulated total food aid required is 2 373, as outlined in Table 4.4, which is lower than the total requirement of 2 672 total simulated aid when all regions receive aid set at 8, as outlined in Table 4.3.

Comparing scenarios with varying food aid available in each region, may help determine where available food aid can be reallocated, without impacting the overall populations' FCS recovery, following a shock. The scenarios where the amount of food aid varies in each region, are used to determine if less total food aid may result in high levels of recovery, in terms of percentage of households that recover or are recovering from a shock.

Different amounts of monthly food aid in each region, may require much less total food aid, while resulting in similar high levels of recovery, in this case over 97 percent, as demonstrated in Table 4.5, helping to evaluate the trade-off between the cost of recovery and percentage of the population that recovers to an acceptable level.

Amount of monthly food aid available			Food aid requirement and recovery	
Northern Region	Central Region	Southern Region	Percentage of households that recovers to FCS > 42	Estimated simulated total food aid required
6	6	4	97.4	1 705
6	4	6	98	1 717
4	6	6	99.8	1 922
6	6	6	99.8	2 004
8	6	6	99.8	2 089

Table 4.5: *Percentage of the population whose Food Consumption Score recovers from a shock, subject to varying amounts of food aid available per household, for each region.*

The regional FCS trends from the seven scenarios with varying levels of food aid, outputted in Step 2(c), are used in Step 3, to rank the regions in terms of their quantified resilience to food insecurity, as described in §4.1.3.

4.1.3 Resilience to food insecurity metrics for Malawi

The distribution of each FCS trend for each region from the seven scenarios, are fitted in Step 3(a), to integrate the FCS PDFs in Step 3(b), and to derive resilience to food insecurity metrics in Step 3(c), and ultimately to rank and describe the regions in Step 3(d), in terms of selected metrics.

The FCS distributions are fitted in Step 3(a) using the 'gamlss.dist' package, in the statistical programming tool, R [28], as shown in Appendix E.1. Of the 28 FCS trends, 4 fit a generalized gamma (GG) distribution, 6 fit a gamma (GA) distribution, 4 fit a Weibull (WEI) distribution, 2 fit a Weibull 3 (WEI3) distribution and 4 fit an inverse Gaussian (IG) distribution, 6 fit a Box-Cox Power Exponential (BCPE) distribution and 2 fit a Box-Cox Cole and Green (BCCG) distribution.

The gamlss.dist package tests for distributions that may be used to model response variables in Generalised Additive Models for Location Scale and Shape, and recommends the distribution with the best fit according to a number of measures.

The FCS PDFs from each scenario for each region, with the parameters outlined in Table 4.6, are integrated in Step 3(b), as shown in Appendix E.2, using equations (2.3), (2.4) and (2.5) and the respective distribution function from equations (2.6) to (2.12), to derive resilience to food insecurity metrics.

Food aid	Malawi	Northern Region	Central Region	Southern Region
0	GG $\mu = 32.5$ $\sigma = 0.02$ $\nu = 103.1$	GA $\mu = 36.4$ $\sigma = 0.04$	GA $\mu = 33.4$ $\sigma = 0.06$	BCPE $\mu = 33.6$ $\sigma = 0.03$ $\nu = -8.1$ $\tau = 5.5$
2	BCPE $\mu = 34.8$ $\sigma = 0.04$ $\nu = 1$ $\tau = 0.3$	GG $\mu = 38.7$ $\sigma = 0.01$ $\nu = 422.3$	BCPE $\mu = 34.8$ $\sigma = 0.04$ $\nu = 0.5$ $\tau = 7.1$	GG $\mu = 35.2$ $\sigma = 0.01$ $\nu = 24.9$
4	BCPE $\mu = 36.7$ $\sigma = 0.05$ $\nu = 4.7$ $\tau = 0.3$	BCCG $\mu = 39.3$ $\sigma = 0.04$ $\nu = 27.5$	BCPE $\mu = 36.5$ $\sigma = 0.06$ $\nu = 0.43$ $\tau = 0.3$	BCPE $\mu = 35.8$ $\sigma = 0.08$ $\nu = 15.7$ $\tau = 0.6$
6	WEI $\mu = 38.5$ $\sigma = 19.05$	BCCG $\mu = 37$ $\sigma = 0.41$ $\nu = 16.07$	GG $\mu = 39.2$ $\sigma = 0.03$ $\nu = 58.9$	WEI $\mu = 37.6$ $\sigma = 16.4$
8	WEI3 $\mu = 38.6$ $\sigma = 12.9$	WEI $\mu = 43.2$ $\sigma = 13.8$	WEI3 $\mu = 38.7$ $\sigma = 13.6$	GA $\mu = 37.8$ $\sigma = 0.09$
10	GA $\mu = 39.8$ $\sigma = 0.12$	WEI $\mu = 44.3$ $\sigma = 10.7$	GA $\mu = 40$ $\sigma = 0.11$	IG $\mu = 38.9$ $\sigma = 0.02$
12	IG $\mu = 41.1$ $\sigma = 0.02$	GA $\mu = 43.5$ $\sigma = 0.13$	IG $\mu = 41.5$ $\sigma = 0.02$	IG $\mu = 40.1$ $\sigma = 0.02$

TABLE 4.6: *Food Consumption Score distribution parameters for each region and for Malawi, subject to different levels of food aid available per household.*

The resilience to food insecurity metrics outputted in Step 3(c), include the Center of Resilience, ρ_Q, Resilience Bandwidth, χ_Q, and Resilience Skewness, ψ_Q, and are derived for each region and Malawi overall. The quantified resilience metrics are used in Step 3(d) to rank the regions in terms of their recovery capacity, or rather resilience to food insecurity.

Regions may be described and ranked by their recovery duration, or rather their chance of recovery, using ρ_Q, by the dispersion of their recovery progress, using χ_Q, or by their pace of recovery, using ψ_Q, as outlined in Table 3.5.

The most suitable metric for ranking regions is ρ_Q, as it describes the chance of recovery, where higher values of ρ_Q indicate a higher chance of recovery [27]. Regions with lower values of ρ_Q should be prioritised for food aid, as they have a lower chance of recovery.

A suitable metric for ranking regions when concerned with the amount of food aid that is required over time is χ_Q. Higher values of χ_Q indicate recovery is more dispersed or spread over time, thus a stable amount of food aid is required, where lower values indicate most of recovery happens over a short period of time, thus varying amounts of food aid over the recovery duration, are required.

A suitable metric for ranking regions when concerned with when food aid is required, is ψ_Q, particularly the algebraic sign of ψ_Q. Negative values indicate the pace of recovery is quicker during the first half of the recovery progress, than the second half, thus more food aid is required during the second phase of recovery, when the pace of recovery slows down. Positive values of ψ_Q indicate the pace of recovery is quicker during the second half of the recovery progress, than the first half [27].

The magnitude of ψ_Q indicates the degree to which the pace of recovery slows down or speeds up during the second phase of the recovery progress, where higher values indicate a more fluctuating pace of recovery and lower values indicate a more steady pace [27].

The regional ρ_Q, χ_Q and ψ_Q metrics derived from each scenario, as outlined in Table 4.7, are to describe and rank each region in terms of their resilience to food insecurity.

Food aid	Metric	Malawi	Northern Region	Central Region	Southern Region
0	$\rho_Q =$	60.7	63.2	61.7	61.9
	$\chi_Q =$	16.9	15.5	16.4	16.3
	$\psi_Q =$	−26.32	−28.2	−26.7	−15.9
2	$\rho_Q =$	62.3	63.6	62	62.3
	$\chi_Q =$	16	15.2	15.9	16
	$\psi_Q =$	−21.7	−33.5	−54.5	−10.7
4	$\rho_Q =$	63.3	64.6	62.2	62.9
	$\chi_Q =$	15.4	14.7	15.5	15.7
	$\psi_Q =$	−40.6	−24.2	−56.3	−39.3
6	$\rho_Q =$	63.7	65.1	63.9	63.1
	$\chi_Q =$	15.3	14.5	15.1	15.6
	$\psi_Q =$	−84.1	−95.6	−59.6	−108.6
8	$\rho_Q =$	64.2	65.7	64.2	63.8
	$\chi_Q =$	15.1	14.2	15	15.3
	$\psi_Q =$	−189.4	−184.1	−171.4	−147.5
10	$\rho_Q =$	64.7	65.8	64.8	64.2
	$\chi_Q =$	14.9	14.2	14.8	15.1
	$\psi_Q =$	−237.6	−346.2	−232.9	−280.3
12	$\rho_Q =$	65.3	66.4	65.5	64.8
	$\chi_Q =$	14.6	13.9	14.5	14.8
	$\psi_Q =$	−313	−349.2	−318.6	−298

TABLE 4.7: *Resilience to food insecurity metrics for different levels of food aid, for all regions.*

In terms of the duration of recovery, or chance of recovery, Malawi overall has the highest chance of recovery when food aid is set to 12, indicated by the higher value of ρ_Q, as outlined in Table 4.7 and shown in Figure 4.7.

The incremental increases in ρ_Q, as the amount of food aid available increases, grow smaller, as outlined in Table 4.7 and shown in Figure 4.7, indicating that increase in the chance of recovery due to the increase in food aid available, reaches a threshold, in this case when food aid available is around 12. The chance of recovery in all regions, increases only slightly when the amount of food aid available increases from 10 or 12, as outlined in Table 4.7 and shown in Figure 4.7.

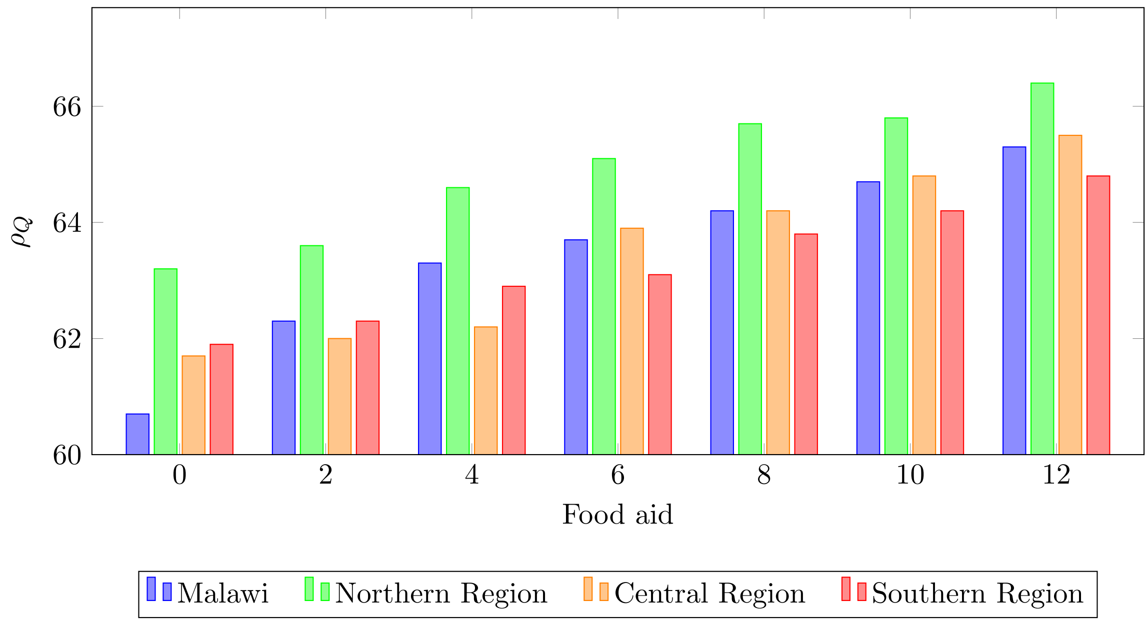


FIGURE 4.7: *Center of resilience for different levels of food aid, for all regions.*

The Northern Region has a much higher chance of recovery in each scenario, than the Central Region and Souther Region. The Southern Region has a higher chance of recovery than the Central Region when food aid available per household is set to $0, 2$ or 4. When however food aid available per household is set to $6, 8, 10$ or 12, the Southern Region has the lowest overall chance of recovery as outlined in Table 4.7 and shown in Figure 4.7.

The lower values of ρ_Q in the Southern Region, which is typically the most food insecure region in Malawi, as conveyed in the 2019 IPC report [30], indicate that food aid in the Southern Region should be prioritised over food aid in the Northern Region and Central Region.

In terms of the dispersion of the recovery progress, the recovery progress for Malawi overall is most dispersed when food aid is set to 0, indicated by the higher value of χ_Q, as outlined in Table 4.7 and shown in Figure 4.8. The dispersion of the recovery progress decreases as food aid increases, as outlined in Table 4.7 and shown in Figure 4.8, corresponding to the more evened out gradient in the FCS trend as food aid increase, as shown in Figure 4.5.

The dispersion of the recovery progress is least dispersed in the Northern Region, which is typically the least food insecure region in Malawi, as conveyed in the 2019 IPC report [30], indicated by the lower values of χ_Q, as outlined in Table 4.7 and shown in Figure 4.8. The dispersion of the recovery progress is most dispersed in the Southern Region, indicated by the higher values of χ_Q, which suggests the amount of food aid available over the recovery duration, should be more stable in the Southern Region, than in the other regions, where the amount of food available may vary over the recovery duration.

In terms of the pace of recovery, the pace is quicker during the first half of the recovery phase than the second half, across Malawi, for all scenarios, indicated by the negative values of ψ_Q, as outlined in Table 4.7. This indicates that more food aid is required during the second half of the recovery phase than the first, as the pace in recovery slows down during the second half, to speed up recovery.

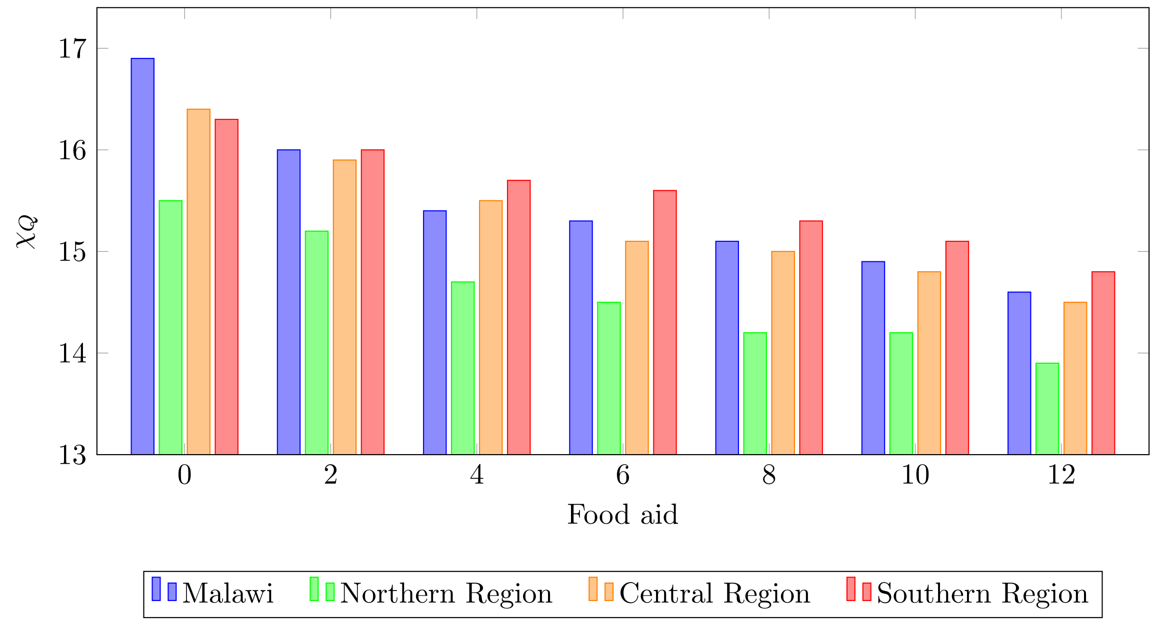


FIGURE 4.8: *Resilience bandwidth for different levels of food aid, for all regions.*

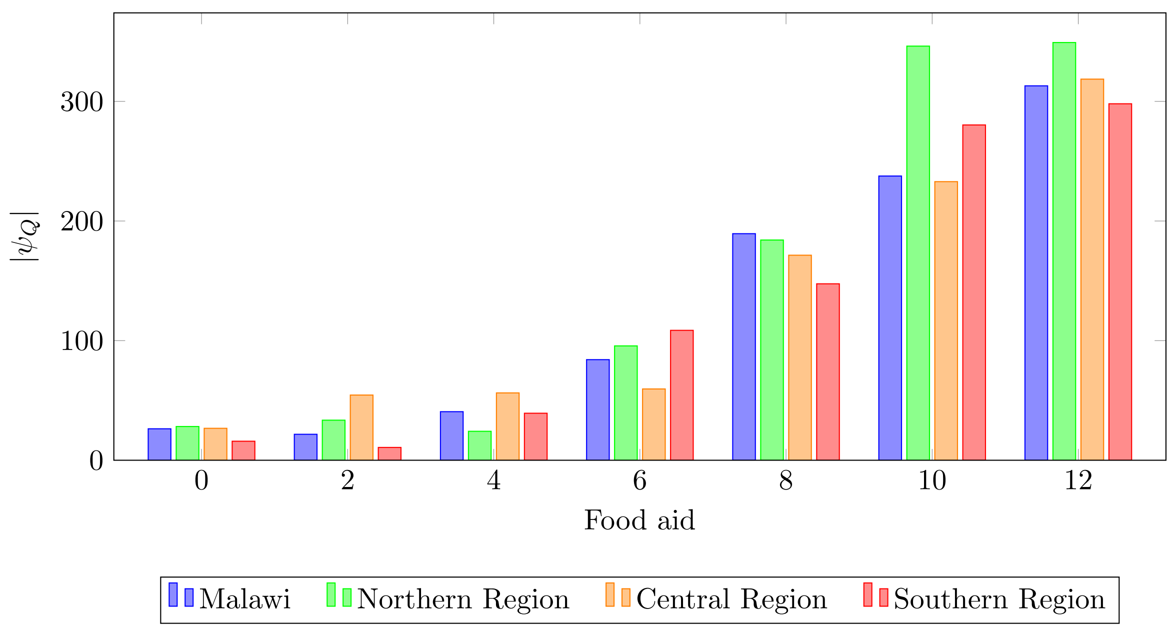


FIGURE 4.9: *Resilience skewness magnitude for different levels of food aid, for all regions.*

The change in the pace of recovery from the first half of the recovery phase to the second half, is most steady when a smaller amounts of food aid per household is available than when larger amounts are available, indicated by the smaller magnitude of ψ_Q, as outlined in Table 4.7 and shown in Figure 4.9. This suggests that the pace in recovery in the second phase, slows down more in the second half of the recovery phase when more food aid is available, as majority of the recovery progress is completed in the first half.

In terms of resilience to food insecurity, the Northern Region is considered to be most resilient, as it generally has the highest chance of recovery, or higher values of ρ_Q, as shown in Figure 4.7. The recovery progress is least dispersed over time, with lower values of χ_Q, as shown in Figure 4.8.

The Southern Region, on the contrary, is considered to be the least resilient to food insecurity, as it generally has the lowest chance of recovery, or lower values of ρ_Q, as shown in Figure 4.7 and outlined in Table 4.7, where the recovery progress is most dispersed over time, with higher values of χ_Q, as outlined in Table 4.7 and shown in Figure 4.8.

The Central Region is more resilient to food insecurity than the Southern Region, in terms of the chance of recovery, when food aid available per household is set to $6, 8, 10$ or 12, indicated by the higher values of ρ_Q.

In terms of the pace of recovery, where higher values of ψ_Q indicate a more fluctuating pace from the first half of the recovery phase to the second half, the Northern Region is least resilient when food aid available per household is set to $0, 8, 10$ or 12, while the Central Region is least resilient when food aid available per household is set to 2 or 4, as outlined in Table 4.7 and shown in Figure 4.9.

The resilience to food insecurity model is used to assess the impact of varying amounts of food aid on a populations' FCS, subject to selected model parameters, particularly those describing the shock impact. Adjusting the model parameters may improve the representation and validity of model results, as discussed in §4.2.

4.2 Sensitivity of model parameters

A number of parameters in the FCS simulation model, used to estimate a populations' change in FCS, may be adjusted a number of ways, which may lead to different results. The model parameters adjusted in this study include the amount of monthly food aid available in each region, however, the shock parameters, in terms of the shock magnitude and scale of impact, may also potentially be adjusted, to compare the impact of a more representative range of shocks, as discussed in §4.2.1. Adjusting the number of simulations runs K, as discussed in §4.2.2, may improve simulation representation of the actual data. The size of the grid cells in the NetLogo model will impact how many grid cells cover each region, which impacts the number of households N, that may be placed on the landscape, as discussed in §4.2.3.

4.2.1 Shock impact and occurrence

The simulated shock in the food security simulation model may be adjust a number of ways, such as changing the shock occurrence, increasing the number of shocks that occur over a simulation, varying the scale of impact in terms of regions affected, the magnitude of impact, or a combination of ways. Varying the frequency, scale and impact of the shock may help create a number of potential shock profiles to compare.

For example, having a shock that occurs in June, or at around day 150, as opposed at the start of the simulation in January, would enable the analysis of various shock profiles. A shock profile analysis would require data collected over an extended period of time, following actual shocks.

Since this study is concerned with quantifying a populations' resilience to food insecurity, ideally time series captured over a long period of time, and during an actual shock, may be used to model a populations' resilience to food insecurity, without the need to gauge different potential shock profiles. This study uses estimates of the magnitude of a shock μ, variance σ and time instance of a shock t_I, for demonstrative purposes in modelling resilience to food insecurity, and does not adjust these shock parameters.

4.2.2 Number of simulation runs

For each simulation setting, the model completes $K = 100$ number of repetitions, where the average of all 100 repetitions are recorded and used for further resilience analysis. The selection of K will depend on the sample size of the survey data, and the desired accuracy of sampled data in the simulation, in terms of selected statistics.

To determine an acceptable number of simulation repetitions K, the model is simulated a number of times, where food aid is equal to 0, and the statistics of simulation results for the monthly average FCS of Malawi overall, are compared to the actual survey data, as shown in Table 4.8.

Considering the simulated averages and standard deviations when $K = 100$ number of repetitions are within 0.1 of the averages and standard deviations of the actual survey data, as shown in Table 4.8, this study takes $K = 100$ as an acceptable number of simulation repetitions.

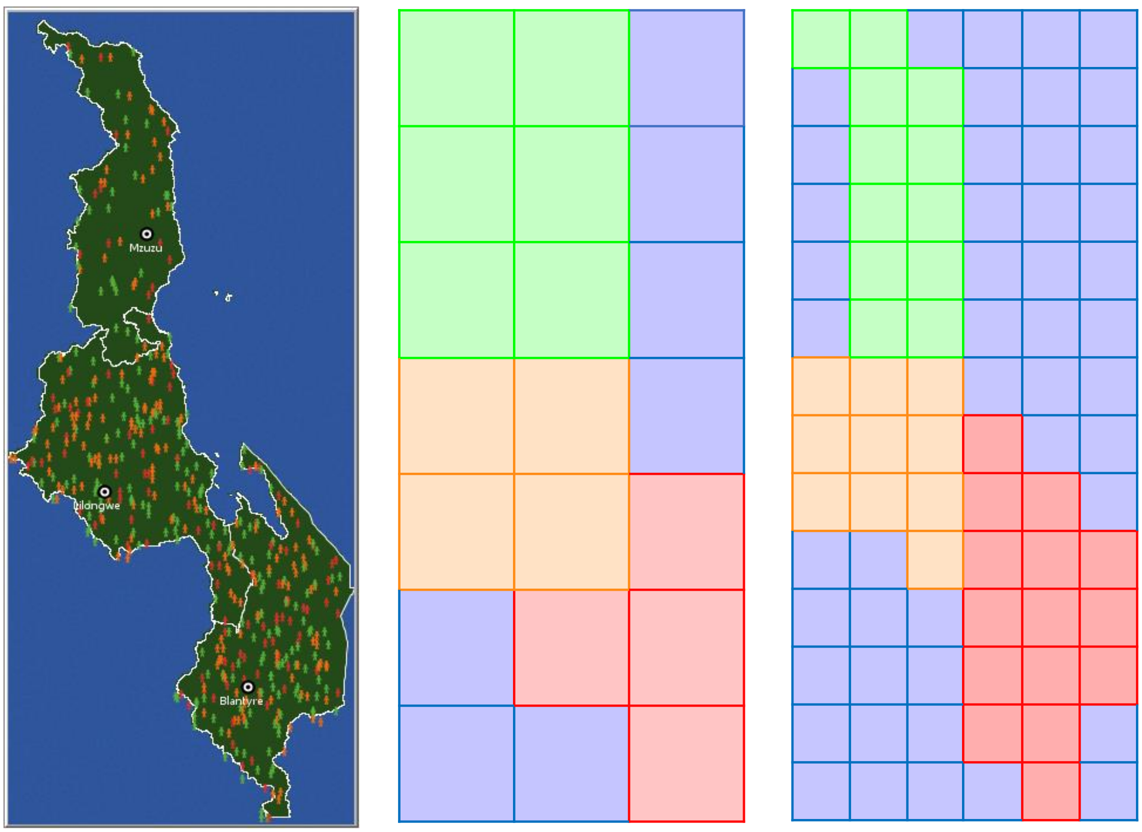
	Month	Minimum	Medium	Maximum	Average	Standard deviation	Variance
Survey data	1	0	51.5	112	52.4	20.4	415.9
	2	5.5	54	112	55.3	21.5	463
	3	2	50.5	112	52	20.9	437.2
	4	1	49	112	51.8	20.9	436.9
k = 10	1	7.5	51.5	110	53.3	21.2	449.8
	2	7	54	112	54.6	21.2	448.2
	3	3	50.5	112	51.8	20.9	435.6
	4	3	49	112	51.6	20.7	431.6
k = 100	1	0	51.3	112	52.5	20.5	419.3
	2	5.5	54	112	55.3	21.5	463.6
	3	2	50.5	112	51.9	20.8	439.2
	4	1	49.5	112	51.9	20.8	435.4
k = 1000	1	0	51.5	112	52.4	20.4	416.7
	2	5.5	54	112	55.2	21.5	462.6
	3	2	50.5	112	52	20.9	434.6
	4	1	49	112	51.8	20.8	433.5

TABLE 4.8: *Simulation statistics describing the monthly average Food Consumption Score (FCS), to help determine an acceptable value for the number of simulation runs K.*

4.2.3 Size of grid cells and regional boundaries

The landscape shown in Appendix C.1 is a 181×601 grid of cells, where each of the 108 781 grid of cells represents 1.4 km^2. The grid cells cover either one of three regions, neighbouring countries or water. Malawi extends 257 km east to west and 853 km north to south, with an area of 118 480 km^2, of which 24 400 km^2 consists of water, chiefly Lake Malawi [20].

A high ratio of 1 : 217, in the number of grid cells, 108 781, to the number of agents, 500, suggests that the model may test experiments for a greater number of households N. The model results in this case are not sensitive to the size of the grid cells, as the households placed on the landscape do not interact with one another and are therefore not influenced by the regional density. Increasing the regional density, by increasing the number of sampled households N, may improve the representation of the simulated results, subject to the survey sample size.



(a) 181 x 601 (b) 3 x 7 (c) 6 x 14

FIGURE 4.10: *Number of grid cells and the grid cell size selection comparison.*

The size of the grid cells also effects the resolution of the landscape display, in this case the map of Malawi, as shown in Appendix C.1, and will impact how many grid cells cover each region.

The resilience to food insecurity regional comparisons, outputted in Step 3(d), as discussed in §4.1.3, are compared alongside previous literature findings, to verify the interpretation of results and to demonstrate how the resilience metrics may complement food security analysis, as discussed in §4.3.

4.3 Comparing results with literature

The resilience to food insecurity results indicated that the Northern Region is most resilient to food insecurity while the Southern Region is least resilient. The resilience metrics and result findings not only correspond to previous food security analyses, but may be used by governments and their development partners to help prioritise food aid intervention for maximum impact on food security, or to increase the chance of FCS recovery, following a shock.

According to previous literature on food security in Malawi, the Southern Region is typically the most food insecure region in Malawi, as conveyed in the 2019 IPC report [30], as well as in the 2012 Comprehensive Food Security and Vulnerability Analysis (CFSVA) [36] and the 2014 Integrated Context Analysis (ICA) [37], as outlined in Table 4.9. This corresponds to the resilience to food insecurity results, where the Southern Region is the least resilient to food insecurity, compared to the Northern Region and Central Region.

Region	Simulated average food insecure population	Simulated percentage of region food insecure	Average food insecure population from 2009 to 2013 [37]	Percentage of households with food shortages in 2012 [36]
Northern Region	41	63	±298 000	27
Central Region	143	67.4	±461 000	24
Southern Region	150	67.4	±889 000	38
Malawi	334	66.8	±1 640 000	31

Table 4.9: *Estimated regional food insecure population simulation and literature comparison.*

Considering the regions where resilience to food insecurity analyses have been conducted, the Southern Region is generally more disaster prone and consequently has had more food aid interventions than the other regions. Between 2016 and 2017, seven resilience to food insecurity studies were applied in the Southern Region, while two were applied in the Central Region and only one was applied in the Northern Region, as illustrated in Figure 2.2.

The typically lower level of food security in the Southern Region corresponds to the resilience to food insecurity findings, where the Southern Region has the lowest chance of recovery, while the progress of recovery is most dispersed over time.

The resilience to food insecurity metrics may supplement food security analyses by quantifying a groups' capacity to recover from shocks. Quantified metrics allow decision makers to compare and rank different groups, the same groups over time, or the same groups in different scenarios, in terms of their resilience to food insecurity, to better prioritise food aid intervention.

Where the CFSVA, ICA, IPC and RIMA-II models require data covering a range of influences, as illustrated in Appendix A.1, the resilience to food insecurity model uses a single composite metric, particularly the FCS, and may therefore be conducted over a larger scale.

In addition the FCS may be collected using mobile technology, allowing for higher frequency data collection than previous resilience to food insecurity models. The MIRA model requires 15 minute interviews, which decreases the ability of data collection in the same amount of time, and increases the need for data processing, where the CATI surveys can be collected remotely and frequently.

The national scale food security analyses, such as the CFSVA, ICA and IPC are conducted less frequently than mobile surveys, due to intensive data collection requirements, where community scale analyses allow for more frequent data collection, but are conducted at a smaller scale.

The proposed resilience to food insecurity model is beneficial, as it uses mobile food security survey data, to enable high frequency and wide-scale data collection, and ultimately to enhance resilience to food insecurity analysis, as concluded in Chapter 5.

CHAPTER 5

Conclusion

"The Global Report on Food Crises shows the magnitude of today's crises but also shows us that if we bring together political will and today's technology, we can have a world that's more peaceful, more stable and where hunger becomes a thing of the past."

- David Beasley, *WFP Executive Director [30]*

Contents

The defined resilience to food insecurity metrics enable governments and development partners to quantify and rank a population in terms of their response capacity to shocks, as discussed in §5.1. Lessons learned from the research process are discussed in §5.2, to guide future work.

5.1 Outcomes

The study primarily set out to define a resilience to food insecurity metric, that captures a populations' ability to recover to an acceptable level of food security, regardless of the studied populations' contextual differences. The methodology described to quantify the defined resilience to food insecurity metrics, as discussed in §5.1.1, may be applied across a range of contexts.

5.1.1 Resilience to food insecurity model

The study ultimately set out to define a populations' resilience to food insecurity, using a composite food security indicator, in this case the Food Consumption Score (FCS), to enable development actors to quantify and rank a population in terms of their recovery capacity, across a range of contexts. Prerequisite objectives include defining the FCS metric and developing a FCS simulation model to estimate a populations' FCS trend, following a shock.

The study outcomes meet the three objectives described in Chapter 1, most notably:

1. A food security indicator that captures the effect of multiple livelihood capabilities on a populations' food consumption, specifically the FCS, is defined in §2.4.1. The FCS may be collected using mobile technology, thus may be collected more frequently than previous models, and at a wider scale, which is suitable for resilience analysis.

2. A food security simulation model is developed in § 3.1.2 using NetLogo and R, to monitor and estimate a populations' food consumption trend, following a shock. The model is applied to the Malawi case study to determine the amount of food aid required, for a populations' food consumption to recover to an acceptable level from a simulated shock.

3. A set of resilience to food insecurity metrics that quantify a populations' ability to recover to an acceptable level of food security is defined in §4.1.3. A description of calculated resilience metrics from a Malawi case study, demonstrate how development actors may quantify and rank, a population in terms of their resilience to food insecurity.

5.2 Future work

The lessons learned throughout the course of this study, as outlined in §5.2.1, may help to guide future resilience analysis, while recommendations for future work suggest alternative methods to analysing resilience to food insecurity, as outlined in §5.2.2.

5.2.1 Lessons learned

To analyse a populations' resilience to food insecurity, only the change in a selected food security state variable over time, in this case the FCS, is required. Factors influencing the FCS, such as people interaction, particularly borrowing, buying and selling food, are not required for analysis when the desired outcome variable is captured directly.

Resilience analysis focuses more on historical and real-time data than on trying to project data using indicator variables. While indicators such as income may influence a households food security, the exact impacts of income following a range of possible shocks, are less predictable, where markets may be inaccessible due to road closure from floods, or food may not be affordable due to political instability and inflation. To expand the model to forecast FCS trends following a trend, data collected over an extended period of time, and following actual shocks, may be used to create various shock profiles, to enhance food aid planning.

Ultimately, the fundamental concern when deciding how much food aid people require, when and where, is their food consumption, especially following a shock, such as flood or drought for example.

To analyse a populations' income, for example, a resilience to financial insecurity model may be applied in a similar manner to that of the resilience to food insecurity model, by looking at, say, expenditure.

Following an IBM approach allows decision analysts to disaggregate the model data by selected attributes, for example by income, gender or beneficiary status as well as by region, since the data is modelled at an individual level. The data may also be updated in real-time without the need to refit distributions to sample data.

5.2.2 Recommendations

In conclusion, to improve future resilience to food insecurity analyses that employ the proposed methodology, noteworthy considerations are recommended, namely:

1. Comparing experiments that vary the simulated shock in terms of frequency, intensity or scale, may improve resilience analysis, as different shock profile settings may lead to different FCS trend results, which may be a better representation of the impact of actual random shocks.

2. Rather than using the FCS Probability Density Function (PDF) for resilience analysis, a FCS Probability Mass Function (PMF), also proposed by Sharma et al [27], may be used to integrate step functions, where there is discontinuity in the FCS recovery curve.

3. Applying data that is collected over a longer period of time, over a year for example, may allow for forecasting methods to be applied, to enable the estimation of the FCS by evaluating the change in a populations' FCS, throughout an agricultural seasonal.

4. Resilience analysis may be applied at a higher or lower administrative level, such as a international level, comparing countries' resilience to food insecurity globally, or a local district level.

5. Disaggregating data by attributes, such as the sex of the household head, receipt of food aid, or even by the amount of food aid received, may help to determine a suitable food aid schedule.

6. Reporting on the composition of the FCS, in terms of the defined food groups, may help to determine a suitable food aid basket, in terms of the required food groups.

7. Use the coping strategy index (CSI) metric as a state variable to model resilience to food insecurity, in conjunction with the FCS, to indicate whether the households' food security status is declining or improving over time.

8. Use the NetLogo spatial grid to assess whether the change in FCS of selected neighbouring households, has a significant impact on the change in FCS of selected households.

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APPENDIX A

Food security indicators

A.1 Food security reporting indicators

Common food security indicators collected for the food security analyses, as discussed in § 2.1, are summarised in Table A.1 and Table A.2.

Group of variables	Key variables	Aggregated by Rural/ Urban	Aggregated by Female/ Male
Demographics	- Total population - Headship - Life expectancy - Dependent ratio	Yes	Yes
HIV and AIDS	- Chronic illness - Adult HIV - Primary School drop out	Yes	Yes
Morbidity (children 6-59 months)	- Cough prevalence - Diarrhoea prevalence - Fever prevalence	Yes	Yes
Poverty	- Proportion of household's ultra-poor - Proportion of household's poor	Yes	
Food Insecurity	- Proportion of Food Insecure - Proportion with Survival Deficits - Proportion Requiring Assistance	Yes	Yes
Nutrition Status	- Global Acute Malnutrition (5 - 59 months) - Stunting - Overweight - Obesity	Yes	Yes

Table A.1: *Common food security reporting indicators describing food security.*

Group of variables	Key variables	Aggregated Rural/ Urban	Aggregated Female/ Male
Production (food crops)	- Yield by crop - Quantity by crop	Yes	
Production (cash crops)	- Yield by crop - Quantity by crop	Yes	
Production (livestock)	- Livestock per capita by species - Off take rate by species - Kidding rates	Yes	
Production (fishery and aquaculture)	- Yield per year by species	Yes	
Consumer prices	- Staple food prices (current vs 5YA) - Inflation (current vs 5YA)		Yes
Producer prices	- Staple food prices (5Y trend) - Price by main livestock type		Yes
Crop disease	- Proportion of area affected		
Livestock disease	- Proportion of livestock affected		
Staple cereal availability	- Self-sufficient ratio (surplus/deficit)	Yes	Yes
Food Access	- Food consumption score (FCS) - Coping Strategy Index (CSI) - Household Dietary Diversity Score (HDDS) - Food Insecurity Experience Scale (FIES) - Household Hunger Scale - Food Expenditure Share - Survival Deficit - Livelihood Protection Deficit - Staple Prices - Minimum Acceptable Diet - Proportion of Consumption of iron rich/iron fortified foods	Yes	Yes
Water and Sanitation	- Household access to improved water sources - Household access to improved sanitation	Yes	Yes
Climatic Shocks and Hazards	- Standardized Precipitation Index - Vegetation Condition Index - Fire incidences and area affected - Human and Animal Conflict		

TABLE A.2: *Common food security reporting indicators describing food security, continued.*

A.2 Indicators used in previous RIMA models

The RIMA models applied in previous resilience to food insecurity studies, particularly those applied in Burkina Faso, Niger and Mali, require a range of indicators to evaluate a resilience metric, as outlined in Table A.3.

Pillars	Burkina Faso (1998 and 2003)	Niger (2011)	Mali (2009/2010)
Income and Food Access	- Log of per capita income - Log of per capita expenditure - Food expenditure/Total expenditure	- Weekly total income - Expenditure per capita - Food Consumption Score	
Access to Basic Services	- Improved sanitation - Improved electricity - Potable Water - Distances to services	- Improved sanitation - Improved electricity - Distance to primary school, secondary school, health service, bus stop, bank, services - Infrastructure index	- Electricity, - Improved water facility - Improved toilet facility - Distance to water
Assets	- Tropical Livestock Units (TLU) - Household assets - Crops - Land - Seeds - Extension services - Fertilizers - House - Vehicle assets	- TLU - Wealth index - Expenditure in crop inputs - Land - Improved seeds - Pesticides - Fertilizers - Asset index	- TLU - Wealth index - Household condition index - Land
Sensitivity	- Sensitivity of income	- Number of shocks - Value of livestock - Crop shock: percentage damaged - Share of crop in total income	- Children with malaria - Children with diarrhea - Infibulated women
Adaptive Capacity	- Education of HH head - Livelihood diversification - Per capita labour force	- Education - Livelihood diversification - Food ratio	- Education - Dependency ratio - HH head: wage earner - HH head: farmer - HH head: employer - HH head: no job

TABLE A.3: *Indicators used to describe the analysis components in previous RIMA models [3].*

The studied models in Chapter 2, not only require a food consumption indicator, but also generally require a significantly wider range of other food security indicators, as demonstrated in Table A.4, and are therefore costly and difficult to conduct nationally on a monthly basis.

Category	Food Security Models		Resilience to Food Security Models	
	Integrated Food Security Phase Classification [11]	Comprehensive Food Security and Vulnerability Analysis [36]	Resilience Index Measurement and Analysis [31]	Measurement Indicators for Resilience Analysis [19]
Demography	Population, Mortality, Gender, Age group	Population, Life expectancy, Gender, Age group, Education	Population, Headship, Dependency ratio	Population, Age, Gender
Food access	Food consumption, Food availability, Coping strategies, Dietary diversity, Household hunger scale	Food consumption, Food supplies, Coping strategies, Markets, Food prices, Dietary diversity, Household hunger scale	Food consumption, Food expenditure, Coping strategies, Assets, Household hunger scale	Food consumption, Food expenditure, Assistance needed, Household hunger scale
Nutrition	Stunting, Malnutrition	Stunting, Malnutrition, Illness prevalence	HIV, Overweight, Obesity, Stunting, Malnutrition, Illness prevalence	
Production	Crop yield, TLU	Crop yield, Livestock, Crop disease	Crop yield, Livestock, Crop disease	Crop disease, TLU
Income	Income, Livelihood assets	Income, Livelihoods	Income, Agricultural assets, Land	Number of houses, Land
Risk exposure	Disaster risk, Conflict	Disaster risk, Conflict, Precipitation	Shock exposure	Floods, Drought, Number of years in flood plain

TABLE A.4: *Examples of food security information used in previous food security analyses.*

APPENDIX B

Food security survey

B.1 Computer-assisted telephone interview

A mobile food security computer-assisted telephone interview (CATI), conducted by the World Food Programme (WFP), captures household food consumption in question 5 of the survey. Data in this project, is disaggregated by region, captured in question 3 of the survey [33].

I. **Geographic and demographic information**

1. Is the head of your household a man or woman?
2. In what year were you born?
3. Which district of Malawi are you currently living in?
4. Do you live in a boma or a city or a village?

II. **Food security indicators**

5. Consider only meals consumed at home or public kitchen but not in private restaurants or street food. Do not count food consumed in very small amount: i.e. less than a tablespoon per person or consumed by only one member of the household.

   How many days in the past 7 days did your household eat food from the following food groups?

   (a) Cereals, grains, roots and tubers including rice, pasta, bread, sorghum, maize, potato, white sweet potato, cassava.
   (b) Pulses, nuts and seeds including sugar beans, dried peas, groundnuts, lentils, nuts and soy.
   (c) Vegetables including onion, tomatoes, carrots, beans, mushrooms, pumpkin, pumpkin leaves, orange sweet potatoes, cassava leaves, beans leaves and okra.
   (d) Fruits including banana, apple, lemon, mango, papaya, apricot, peach, guava, avocado and oranges.
   (e) Meat, eggs and fish including goat, beef, chicken, pork, bush mice, bush meat, kidney, heart, other organ meats and canned tuna.

(f) Milk and other dairy products including sour milk and yoghurt. Excluding margarine, butter and small amounts of milk for tea or coffee.

(g) Oils and fats including vegetable oil and margarine.

(h) Sugar and sweets including honey, jam, cakes, candy, cookies and sugary drinks.

III. **Consumption-based coping strategies**

6. How many days in the past 7 days did your household eat foods you enjoy less, because it was cheaper?

7. How many days in the past 7 days did your household get food or money to buy food from family or friends?

8. How many days in the past 7 days did your household eat fewer meals in a day?

9. How many days in the past 7 days did your household eat smaller meals?

10. How many days in the past 7 days did adults in your household eat less so children can also eat?

IV. **Other**

11. In the past 30 days, what was the main source of cereals (nsima, cassava, sorghum or rice)?

    (a) Own production.
    (b) Purchases.
    (c) Gifts.
    (d) Food assistance.
    (e) Other.

12. Did your household receive food assistance in the past 30 days?

13. What is the typical day's wages for unskilled casual manual labour (Ganyu)?

14. What kind of wall does your house have?

    (a) Cement.
    (b) Mud.
    (c) Baked bricks.
    (d) Unbaked bricks.

15. How many active/functional mobile phones (working SIMs) does your household use?

16. What is the main problem your household or community faces with accessing food?

APPENDIX C

Food security simulation

C.1 Food security simulation model interface

The interface of the food security model, simulated in NetLogo, is shown in Figure C.1.

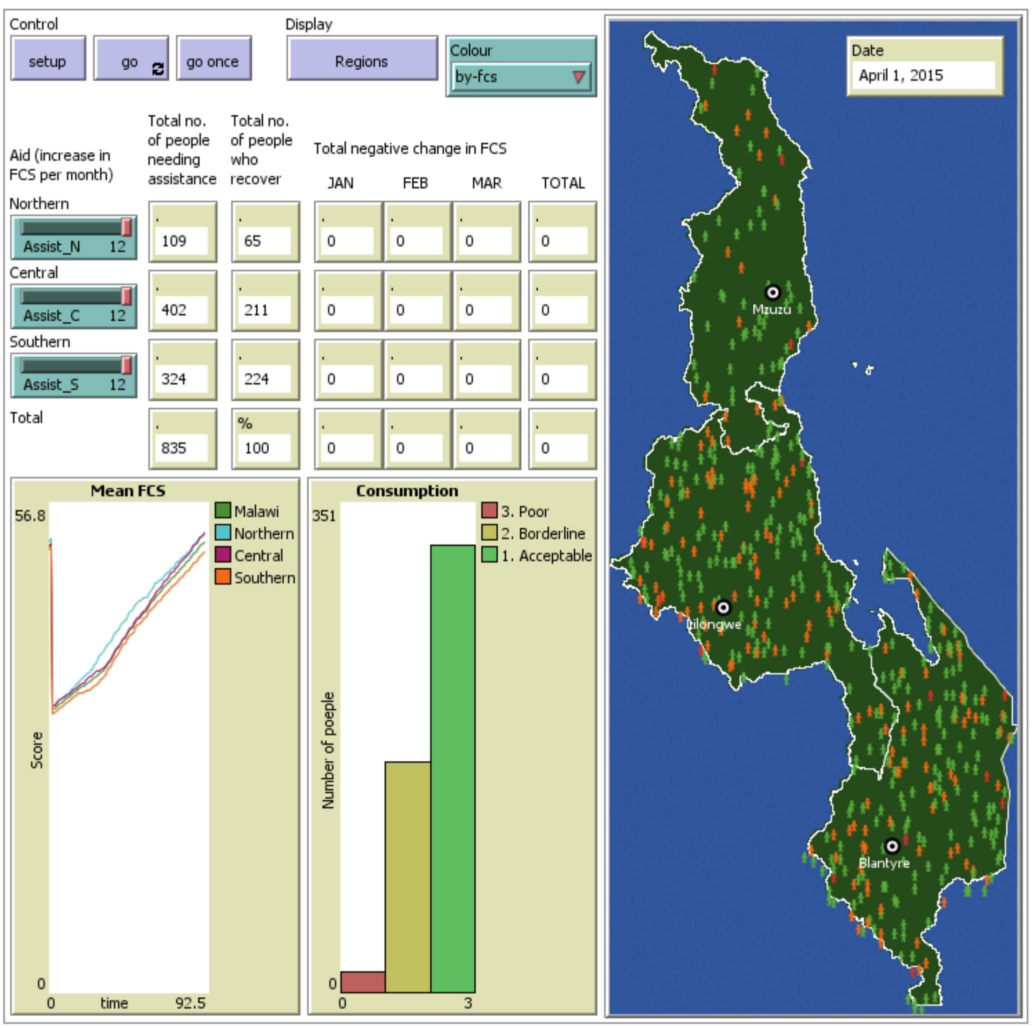

FIGURE C.1: *Food security simulation model NetLogo interface.*

C.2 Food security simulation model code

The food security model code, simulated in NetLogo and outlined in Algorithm 1, as shown in Figure C.2, provides a detailed account of the simulation process.

```
; - - - - - - - - - - - - GLOBALS - - - - - - - - - - - -
extensions [ gis csv time table ]
globals [ start_date current_date month day reg_shp reg_ras input ]
breed [ people person ]
breed [ regions region ]
patches-own [ reg_code ]
people-own [ home_reg fcs fcs_status fc1 fc2 fc3 fc4 bc1 bc2 bc3 c1 c2 c3 rec ]
regions-own [ reg ]
; - - - - - - - - - - - - SETUP PROCEDURES - - - - - - - - - - - -
to setup
  clear-all
  load_datasets setup_patches setup_turtles read_data
  reset-ticks
  set start_date time:create "2015-01-01" ; initialize simulation time
  set current_date time:anchor-to-ticks start_date 1 "days"
  set month time:anchor-to-ticks start_date 1 "months"
  time:anchor-schedule start_date 1 "day"
end
to load_datasets
  set reg_shp gis:load-dataset "region.shp"
  set reg_ras gis:load-dataset "reg.asc"
end
to setup_patches
  gis:apply-raster reg_ras reg_code
  ask patches [ set pcolor blue - 0.25 - random-float 0.25 ]
  ask patches gis:intersecting reg_shp [ set pcolor green - 3 ]
end
to setup_turtles
  foreach gis:feature-list-of reg_shp [ a ->
    let location gis:location-of ( first ( first ( gis:vertex-lists-of a ) ) )
    if not empty? location  [ create-regions 1 [ set xcor gis:property-value a "xc" set ycor gis:property-value a "yc"
                                         set label gis:property-value a "city" set reg gis:property-value a "code"
                                         set shape "city" set color black set size 17 ]
                            create-people gis:property-value a "sam" [ set shape "person" set size 5
                                                                  set home_reg gis:property-value a "code" ] ] ]
end
to read_data
 set input csv:from-file "in.csv"
  ( foreach ( sort people ) shuffle input [ [ pop rsps ] ->
    ask pop [ if home_reg = 1 [ set fc1 item 0 rsps set fc2 item 1 rsps set fc3 item 2 rsps set fc4 item 3 rsps ]
              if home_reg = 2 [ set fc1 item 4 rsps set fc2 item 5 rsps set fc3 item 6 rsps set fc4 item 7 rsps ]
              if home_reg = 3 [ set fc1 item 8 rsps set fc2 item 9 rsps set fc3 item 10 rsps set fc4 item 11 rsps ] ] ] )
    ask people [ set fcs fc1 set c1 fc2 - fc1 set c2 fc3 - fc2 set c3 fc4 - fc3 set bc1 fc2 - fc1 set bc2 fc3 - fc2 set bc3 fc4 - fc3 ]
    ask people [ ifelse c1 >= 0 and c2 >= 0 and c3 >= 0 or fcs >= 42 [ set rec 1 ][ set rec 0 ] ]
    ask people [ if rec = 0 [
                 if home_reg = 1 [ if c1 < 0 [ set c1 c1 + Assist_N ] if c2 < 0 [ set c2 c2 + Assist_N ] if c3 < 0 [ set c3 c3 + Assist_N ] ]
                 if home_reg = 2 [ if c1 < 0 [ set c1 c1 + Assist_C ] if c2 < 0 [ set c2 c2 + Assist_C ] if c3 < 0 [ set c3 c3 + Assist_C ] ]
                 if home_reg = 3 [ if c1 < 0 [ set c1 c1 + Assist_S ] if c2 < 0 [ set c2 c2 + Assist_S ] if c3 < 0 [ set c3 c3 + Assist_S ] ] ] ]
end
; - - - - - - - - - - - - RUN PROCEDURES - - - - - - - - - - - -
to update-fcs-plot
  ask people [ ifelse fcs <=  13 [ set fcs_status "3. Poor" ] [
             ifelse fcs > 13 and fcs <= 42 [ set fcs_status "2. Borderline" ][ set fcs_status "1. Acceptable" ] ] ]
  set-current-plot "Consumption" clear-plot
  let counts table:counts [ fcs_status ] of people
  let score reverse sort table:keys counts let n length score
  set-plot-x-range 0 n let step 0.05 ( foreach score range n [ [ s i ] -> let y table:get counts s let c hsb ( i * 180 / n ) 50 75
  create-temporary-plot-pen s set-plot-pen-mode 1 set-plot-pen-color c
  foreach ( range 0 y step ) [ _y -> plotxy i _y ] set-plot-pen-color black plotxy i y set-plot-pen-color c ] )
end
to go
  if ticks >= 90 [ stop ] ; 3 months
  if ticks = 1 [ ask people [ set fcs fcs - random-normal 20 5 ] ] ; selected shock occurrence
  set day time:get "day" current_date set month time:get "month" current_date
  ask people [ colour_people ]
  move consume
  tick
end
to move
  ask people [ let hr home_reg move-to one-of patches with [ reg_code = hr ] ]
end
to consume
  ask people [ ifelse month = 1 [ set fcs fcs + ( random-normal (c1 / 31 ) 1 ) ][
             ifelse month = 2 [ set fcs fcs + ( random-normal (c2 / 28 ) 1 ) ][ set fcs fcs + ( random-normal (c3 / 31 ) 1 ) ] ]
             if fcs < 0 [ set fcs 0 ] if fcs > 112 [ set fcs 112 ] ]
end
to display_regions
  gis:set-drawing-color white gis:draw reg_shp 1
end
to colour_people
  if Colour = "no-colour" [ set color black ]
  if Colour = "by-fcs" [ ifelse fcs <= 13 [ set color red ] [ ifelse fcs > 20 and fcs <= 42 [ set color orange ][ set color green ] ] ]
end
```

FIGURE C.2: *Food security simulation model NetLogo code.*

APPENDIX D

NetLogo and R input data

D.1 NetLogo input data

Each household in the NetLogo model is initialised with a monthly Food Consumption Score (FCS), based on their home region, sampled randomly from a survey data file, as illustrated in Figure D.1, showing the first 20 lines of the data file. The household FCS is read from a comm separated values (.csv) survey data file, disaggregated by month and region, without column headings. Columns A to D correspond to the FCS in month 1, 2, 3 and 4, respectively, for the Northern Region. Columns E to G correspond to the FCS in month 1, 2, 3 and 4, respectively, for the Central Region. Columns H to L correspond to the FCS in month 1, 2, 3 and 4, respectively, for the Southern Region.

	A	B	C	D	E	F	G	H	I	J	K	L
1	11.5	8.5	14	9	0	5.5	2	7	9.5	8	5.5	5.5
2	16.5	8.5	14	9	0	10	3	7	9.5	8	5.5	6.5
3	16.5	8.5	15	10	0	10	7	8	9.5	12	9	6.5
4	16.5	12.5	15	10	0	11	7	8	9.5	12.5	9.5	13
5	16.5	12.5	17	12	8	12.5	10	8	12.5	14	10	13
6	17	12.5	17	12	16	12.5	10	11	14	14.5	10	13.5
7	17	12.5	17	18.5	16	13.5	10	12.5	15	14.5	10	13.5
8	17	14.5	17.5	18.5	16	13.5	10	13	15	15	10.5	14
9	17	14.5	17.5	19.5	16.5	13.5	10	13	15	16	11.5	14.5
10	19	14.5	17.5	19.5	16.5	13.5	11	14.5	16	16	13	15
11	19	14.5	17.5	19.5	16.5	17.5	12	14.5	16	16.5	14	15
12	19	14.5	17.5	20	16.5	17.5	12	16	16	16.5	14	15
13	19	15.5	18	20	17	17.5	12.5	16	17.5	17.5	14	15.5
14	19	16.5	18	20	17	17.5	14	17.5	19	18.5	14.5	15.5
15	19	16.5	18	20	17.5	18.5	14	18	19	18.5	14.5	16.5
16	22	16.5	18.5	20	17.5	18.5	15	18	19.5	19.5	15	17.5
17	22	16.5	21	22	17.5	19	15	19	19.5	20	16	17.5
18	22	16.5	23	22	17.5	20.5	15	20.5	19.5	20.5	16	18.5
19	22.5	20.5	23	22	18	20.5	16	21	20.5	21	17	18.5
20	22.5	20.5	23.5	24.5	18	20.5	18	21	20.5	21.5	17	18.5

FIGURE D.1: *NetLogo input data file example, showing the first 20 rows.*

D.2 R input data

The calculated average of the FCS trends, for each region from the scenarios with equal food aid, are read into R through a .csv file, as illustrated in Figure D.2, showing the first 30 lines and first 12 columns of the data file. The data file is used for further resilience analysis, as described in Appendix E.1. Columns A to G correspond to the average FCS trend for Malawi for different levels of food aid. Columns H to L correspond to the average FCS trend for the Northern Region, for varying levels of food aid up to food aid set to 8. The remaining 16 columns, M to AB, are not shown in Figure D.2, but similarly correspond to the average FCS trend for the remaining Northern Region scenarios, the Central Region and Southern Region, respectively.

	A	B	C	D	E	F	G	H	I	J	K	L
1	m0	m2	m4	m6	m8	m10	m12	n0	n2	n4	n6	n8
2	32.3	32.4	32.3	32.3	32.3	32.3	32.3	34.1	34.3	34.4	34.6	34.4
3	32.5	32.5	32.5	32.5	32.5	32.5	32.5	34.3	34.5	34.6	34.8	34.6
4	32.6	32.7	32.6	32.7	32.7	32.6	32.7	34.4	34.7	34.7	35.0	34.8
5	32.8	32.8	32.8	32.8	32.8	32.8	32.8	34.6	34.8	34.9	35.2	34.9
6	33.0	33.0	32.9	33.0	33.0	32.9	33.0	34.8	35.0	35.1	35.4	35.1
7	33.1	33.1	33.1	33.1	33.2	33.1	33.1	34.9	35.2	35.2	35.6	35.4
8	33.3	33.3	33.2	33.3	33.3	33.3	33.3	35.1	35.3	35.4	35.7	35.5
9	33.4	33.4	33.4	33.4	33.5	33.4	33.4	35.3	35.5	35.5	35.9	35.7
10	33.5	33.6	33.6	33.6	33.6	33.6	33.6	35.4	35.7	35.7	36.1	35.9
11	33.7	33.7	33.7	33.8	33.8	33.7	33.8	35.6	35.8	35.9	36.3	36.1
12	33.8	33.9	33.9	33.9	33.9	33.9	33.9	35.7	36.0	36.1	36.5	36.3
13	34.0	34.0	34.0	34.1	34.1	34.0	34.1	35.9	36.2	36.3	36.6	36.5
14	34.2	34.2	34.2	34.2	34.2	34.2	34.2	36.0	36.3	36.4	36.8	36.6
15	34.3	34.3	34.3	34.4	34.4	34.3	34.4	36.2	36.5	36.6	37.0	36.8
16	34.5	34.5	34.5	34.5	34.6	34.5	34.6	36.4	36.6	36.8	37.2	37.0
17	34.6	34.6	34.6	34.7	34.7	34.7	34.7	36.5	36.8	36.9	37.4	37.2
18	34.8	34.8	34.8	34.8	34.9	34.8	34.9	36.7	36.9	37.1	37.5	37.4
19	34.9	34.9	34.9	34.9	35.0	35.0	35.0	36.8	37.1	37.3	37.7	37.6
20	35.0	35.1	35.1	35.1	35.2	35.1	35.2	37.0	37.3	37.5	37.9	37.8
21	35.2	35.2	35.2	35.2	35.3	35.3	35.3	37.1	37.4	37.6	38.1	37.9
22	35.3	35.4	35.4	35.4	35.5	35.4	35.5	37.3	37.6	37.8	38.2	38.1
23	35.5	35.5	35.5	35.6	35.6	35.6	35.6	37.5	37.8	38.0	38.4	38.3
24	35.7	35.7	35.7	35.7	35.8	35.7	35.8	37.6	37.9	38.1	38.6	38.5
25	35.8	35.8	35.8	35.9	35.9	35.9	36.0	37.8	38.1	38.3	38.8	38.7
26	35.9	36.0	36.0	36.0	36.1	36.1	36.1	37.9	38.2	38.5	39.0	38.9
27	36.1	36.1	36.1	36.2	36.2	36.2	36.3	38.1	38.4	38.7	39.2	39.1
28	36.2	36.3	36.3	36.3	36.4	36.4	36.4	38.2	38.6	38.8	39.4	39.2
29	36.4	36.4	36.4	36.5	36.5	36.5	36.6	38.4	38.7	39.0	39.6	39.4
30	36.5	36.6	36.6	36.6	36.7	36.7	36.7	38.6	38.9	39.2	39.7	39.6

FIGURE D.2: *R input data file example, showing the first 30 rows and first 12 columns.*

APPENDIX E

R calculations code

E.1 Distribution parameters calculation

The simulated distributions may be fitted using the 'gamlss.dist' package, from the statistical programming tool, R [28]. The data file with the FCS trends, as illustrated in Figure D.2, is read into R, as shown in Figure E.1. An example of how the Food Consumption Score (FCS) distribution parameters of the FCS trend of Malawi, from the scenario where food aid is equal to 0, labelled m0, is shown in Figure E.1. The distributions parameters for each of the studied 28 FCS trends are derived using the same code, as shown in Figure E.1.

```
# Read data
d <- read_excel("data_input.xlsx", sheet=1)
# Select column containing the FCS trend
x <- na.omit(d$m0)
# Fit distribution
xfit <- fitDist(x, k=2, type="realplus", trygamlss=FALSE)
# Summary of distribution parameters
summary(xfit)
# Plot probability density function
pdf.plot(xfit)
```

FIGURE E.1: *R code showing how the distribution parameters of a Food Consumption Score recovery curve is calculated.*

E.2 Resilience metrics calculation

Distributions in the 'gamlss.dist package' include a generalized gamma (GG) distribution, a gamma (GA) distribution, a Weibull (WEI) distribution, a Weibull 3 (WEI3) distribution, and an inverse Gaussian (IG) distribution, among others. An example of how the resilience metrics from the FCS distribution of the Central Region, from the scenario where food aid is equal to 2, is shown in Figure E.2. The distributions parameters for each of the studied 28 FCS trends, as outlined in Table 4.6, are used to derive the resilience metrics for each region in each scenario, using the same code, as shown in Figure E.2.

The first four lines of code specify the distribution parameters derived from the calculated shown in Figure D.2. The p function is used to calculate the probability density of a given function, in this case pGG is used for the GG distribution, as shown in Figure E.2, where pIG, for example, would be used for the IG distribution. The remaining lines of the code are used to calculate the resilience metrics, corresponding to equations (2.3) to (2.5), as shown in Figure E.2.

```
# Calculated distribution parameters
xt <- 90
xmu <- 39.33
xsg <- 0.01
xnu <- 294.87
# Q
xq <- function(xt) {pGG(xt, mu=xmu, sigma=xsg, nu=xnu, log.p=
   FALSE)}
# Rho
xrh <- function(xt) {xt*pGG(xt,  mu=xmu, sigma=xsg, nu=xnu, log.p
   =FALSE)}
# Integrate
xqi <-integrate(xq,0,xt)
xrhi <-integrate(xrh,0,xt)
# Calculate rho metric
Rh <- xrhi$value/xqi$value
# Chi and psi
xch <- function(xt) {((xt-Rh)^2)*pGG(xt, mu=xmu, sigma=xsg, nu=
   xnu, log.p=FALSE)}
xps <- function(xt) {((xt-Rh)^3)*pGG(xt, mu=xmu, sigma=xsg, nu=
   xnu, log.p=FALSE)}
# Integrate
xchi <- integrate(xch,0,xt)
xpsi <- integrate(xps,0,xt)
# Calculate chi and psi metrics
Ch <- xchi$value/xqi$value
Ps <- xpsi$value/xqi$value
# Metrics
Rh
sqrt(Ch)
Ps
```

FIGURE E.2: *R code showing how the resilience metrics of a Food Consumption Score recovery curve is calculated.*